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ARTIFICIAL INTELLIGENCE IN THE LIFE SCIENCES & PATENT ANALYTICS:

MARKET DEVELOPMENTS AND INTELLECTUAL PROPERTY LANDSCAPE

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EXECUTIVE SUMMARY

IP Pragmatics is a technology and IP commercialisation consultancy, with broad expertise across the life sciences. This white paper provides an overview of the market and intellectual property developments for the application of Artificial Intelligence technologies in our key interest areas of Life Sciences, Agriculture and Patent Intelligence.

The deal, market and patent trends demonstrate that Artificial Intelligence (AI) in the life sciences is undergoing rapid growth, especially over the last five years and in particular within the fields of healthcare, drug discovery and agriculture. In addition, the application of AI for patent intelligence for analysis of the technology landscape, is gaining pace.

AI has vast utility for mining large amounts of patient and population health data to address vital gaps in healthcare and clinical workflow. Adoption of AI technologies is reported to have reduced healthcare costs by 50% in pilot testing, while improving patient outcome by over 50%.[1] Pioneering areas for the use of AI in healthcare include robotic-assisted surgery, medical imaging and diagnostics, in particular for fields such as radiology. Hospital workflows are a key application, and virtual nursing assistants are emerging both in a hospital care setting and for the general public, via healthcare specific consumer apps. In the drug discovery arena, venture investment is growing and start-up companies are being established across the US, Europe and Asia. The opportunity to streamline the lengthy and inefficient drug development timelines is a key promise of AI technologies.

Deal flow and funding from Venture Capital and Private Equity firms in the US and Europe is increasing rapidly for AI technology companies within healthcare, drug discovery and agriculture. Industry and investment firms dedicated approximately $5 billion in financing for AI companies across all sectors in 2016. For the healthcare and drug discovery industry approximately $790 million of this was pledged in financing deals for the sector. In parallel, Agritech start-ups have raised over $500 million during the past five years (2012 to 2017) to introduce AI-based solutions that will improve productivity and increase yields. Their technologies range from analysing satellite images to identifying healthy strains of plant microbiome and agriculture robotics.

In terms of key commercial players, the multinational tech companies are leading the way for the healthcare industry. Thereafter, the sector becomes very fragmented with numerous well-funded start-up ventures developing platforms for medical imaging, diagnostics, virtual nursing, personalised medicine, patient monitoring, surgery, hospital workflow and drug discovery, among others. In the field of agriculture, the leading companies are a mixture of software, analytics and hardware start-up companies backed by VCs or industry giants. Start-ups that focus on robotics and machine learning with applications in agriculture started gaining momentum in 2014 and appear to be at the forefront of AI applications in agriculture.

A particular trend for the AI platforms under development is the evaluation of unstructured data such as clinician notes, clinical and research literature and patient data. This trend is

[1] *Healthcare Market Artificial Intelligence and Advanced Analytics*, Research & Markets (2017)

emphasised by the patent analysis conducted in this report, which identified some of the key applications of AI technology. The analysis highlights that patents based on medical imaging analysis and image-based detection methods are prominent. It is therefore unsurprising that companies operating in computing, electronics and imaging represent the majority of patent holders. Key players include **Philips**, **Samsung** and **IBM**, among others. Patent filing has increased rapidly over the last two years, in line with advancements in big data, neural networks, parallel processing and cloud technology. AI technologies are just now becoming mainstream mainly because the hardware and processing technology has caught up with the vision. The critical mass of data needed to "teach" computers now exists and the storage and processing power to execute deep learning are available, fast, and cost-effective.

Partnership is a key theme for the sector. Tech companies are partnering with innovative biotech- and healthcare-focused AI start-ups, as well as hospitals and academic institutions to develop promising, novel solutions. For example, **IBM Watson** recently agreed a $240million deal with **MIT** to create an MIT-IBM Watson AI lab for advancing AI hardware, software and algorithms across industries including healthcare and cybersecurity. The partnership aims to also explore economic and ethical implications of AI to society.[2] Similarly, pharmaceutical companies, which have been historically slower to explore the potential of AI, are establishing research collaborations and undertaking venture financing deals to ensure they can compete in the space in future.

Collaborations and partnerships are also occurring in agriculture. **Monsanto** has recently established a collaboration with **Atomwise**. Atomwise's AtomNet technology will employ powerful deep-learning algorithms and supercomputers to analyse millions of molecules for potential crop protection products. Monsanto has also established a research collaboration with **Second Genome**. The collaboration will leverage Monsanto's extensive genomic databases and Second Genome's expertise in analysing microbial function through metagenomics, protein discovery, machine learning, and predictive analytics to develop next-generation insect-control solutions.

In terms of research, a number of academic laboratories are developing AI technology, for application to the life sciences. Indeed, many of the patent filings in the neural networks and deep learning space of AI across all industries are filed by academic institutions: 40% of assignees filing in 2016 are classified as either a university or research institute.

A search for AI-related research papers identified 621,998 publications across all subject areas and more than 70 countries active in AI research. Publications have increased dramatically from 2001 onwards with machine learning driving innovation and attracting significantly higher attention from researchers comparing to the remaining AI fields described. A geographical analysis of the results correlates with the geographical analysis of the patent search and deal flow, which suggests that the majority of innovation in the field of AI comes from the United States and China.

There are huge commercial possibilities afforded by AI. The key promise of AI as a technology solution is that, in each application, it will gain more experience in the field over time, resulting in continual improvement in precision, efficiency and outcomes. This has

[2] https://arstechnica.com/information-technology/2017/09/ibm-partners-with-mit-for-240-million-fundamental-ai-research-project/

tremendous utility for companies across the life sciences, and ultimately patients themselves.

INTRODUCTION

Artificial Intelligence is an umbrella term for multiple computer science technologies which can be combined in different ways to perform capabilities normally requiring human intelligence. Technologies which form the basis of AI are discussed throughout this report, but broadly fall into the following categories:

- Machine Learning – forms the foundation of AI
- Deep Learning – a sub-sector of machine learning concerned with algorithms based on the structure and function of the human brain
- Computer Vision & Image Recognition
- Natural Language Processing & Speech Recognition
- Cognitive Computing
- Robotics
- Data Mining
- Support Vector Machine
- Social Media Analysis
- Knowledge Representation & Reasoning

These technologies have the capability to: Sense, Comprehend, Act and Learn.[3] AI is essentially a smart solution for compiling and analysing data, taking account of more variables than humans are able to, categorising the new data, predicting trends and ultimately identifying solutions. "Sensing" technologies such as computer vision and audio processing involve perceiving the environment by acquiring and processing images, sounds and speech. "Comprehending" technologies include natural language processing and interference engines which can enable AI systems to analyse and understand the information in knowledge representation. "Act" capabilities of AI allow systems to take action through expert systems technologies, machine learning and inference engines.

Examples of areas where AI has undergone an evolution from automated tasks to problem-solving technologies are: gaming, mathematics, chess and the creation of chatbots capable of having human-like conversation; software-defined intelligence such as predictive analytics using raw numerical data; the emulation of human brain capabilities such as understanding language, speech and sound and interpreting images and videos.[4] The progression and AI categories can be described using the following definitions:[5]

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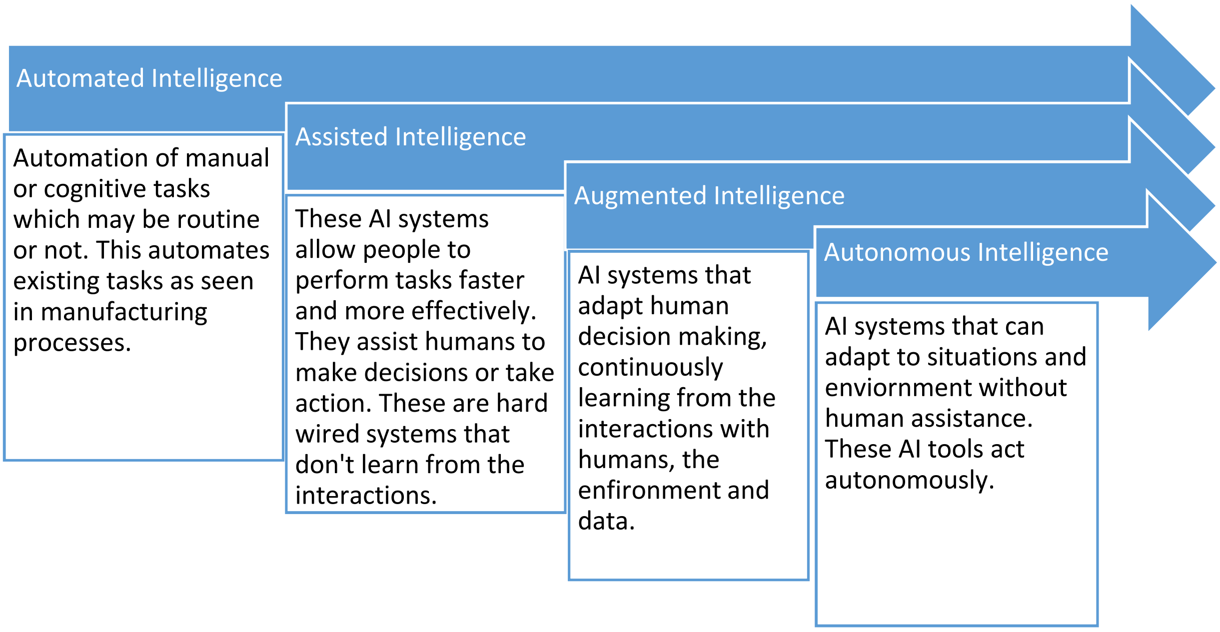
[3] *Why AI is the Future of Growth,* Accenture (2016)

[4] *The Future of AI*, Frost & Sullivan (2016)

[5] *Sizing the Prize, What's the real value of AI for your business and how can you capitalise?* PWC (2017)



The key driving factors enabling the growth of AI solutions across all industries are:[3]

- Computing power – with effectively unlimited access to cloud computing, a market estimated to reach $70 billion in 2015 and an abundance of data storage solutions, the practicalities for AI growth are well established.

- Growth in big data – data is the fuel for AI solutions. Global data has been growing at a compound annual growth rate (CAGR) of >50% since 2010, with increasing connection of devices and digital world solutions. An exponential growth of data is fuelling AI growth.

AI has the potential to disrupt any industry. Those currently at the forefront include transport, telecommunications and retail. Here we focus on the technology as applied to the life sciences industry, the state of the sector and commercialisation opportunities. The key markets analysed in this category are healthcare, drug discovery and agriculture. This is predominantly demonstrated in deal-making activity, as well as patenting and market needs analysis.

AI healthcare systems are one of the fastest growing applications. The market is expected to reach $6.6 billion by 2021, at a CAGR of 40-50%. Platforms are being developed to offer solutions for population health management, patient management, personalised medicine, triaging, surgery and diagnostics. A particularly active, pioneering field is diagnostics and medical imaging, such as AI analysis of CT scans, MRI scans, picture archiving and communications.

The development of AI tools serving the healthcare industry extends to drug discovery, with solutions for identifying and processing promising therapeutic candidates more quickly and effectively than is currently possible, demonstrating the potential to disrupt the commercialisation timelines of the pharmaceutical and biotechnology industries.

Important clinical trials and pilot tests are underway. Solutions already exist for robotic surgery, imaging and diagnostic analysis. However, much needs to happen before clinician and drug development use of the tools are embedded in current industry infrastructure and daily patient care routines. Convincing regulators, healthcare providers and patients to use the tools, as well as prove they are useful and reliable, will be the next big steps for the healthcare and pharmaceutical industries. In parallel, navigating concerns about job automation and questions about reliability of AI algorithms will be essential for the development of the technology and its application across multiple markets.

With burdened healthcare systems across the world and many regions having underserved patient populations, AI is anticipated to play a significant role over the next decade and further in the democratisation of information and distribution of medical resources.

Modern agriculture faces great challenges. According to the UN Food and Agricultural Organisation (FAO), the global population is set to exceed 9 billion by 2050. To feed this growing population, overall food production will need to increase by 70% with available acreage estimated at just an additional 4%. Agriculture needs to increase productivity and efficiency on all levels of agricultural production, while resources like land, water, energy, and fertilisers are becoming scarcer.

Digital technologies and AI applications continue to penetrate agriculture – one of the least digitised industries according to McKinsey research – but at a slower rate compared to other sectors. Available market forecasts appear favourable and point to a strong growth for AI in agriculture in the coming years. The total market for AI systems in agriculture stood at around $168 million in 2015 and is forecast to grow at a CAGR of approximately 23% for the 2017 to 2021 period. The key driving factor for the demand for AI technologies in the agriculture sector is the surge in demand for agriculture robots.

AI coupled with drones, robots and intelligent monitoring systems has been successfully deployed in research and field trials. Machine learning is becoming more mainstream and is set to revolutionise farming by fully automating certain labour activities and management decisions currently made by farmers.

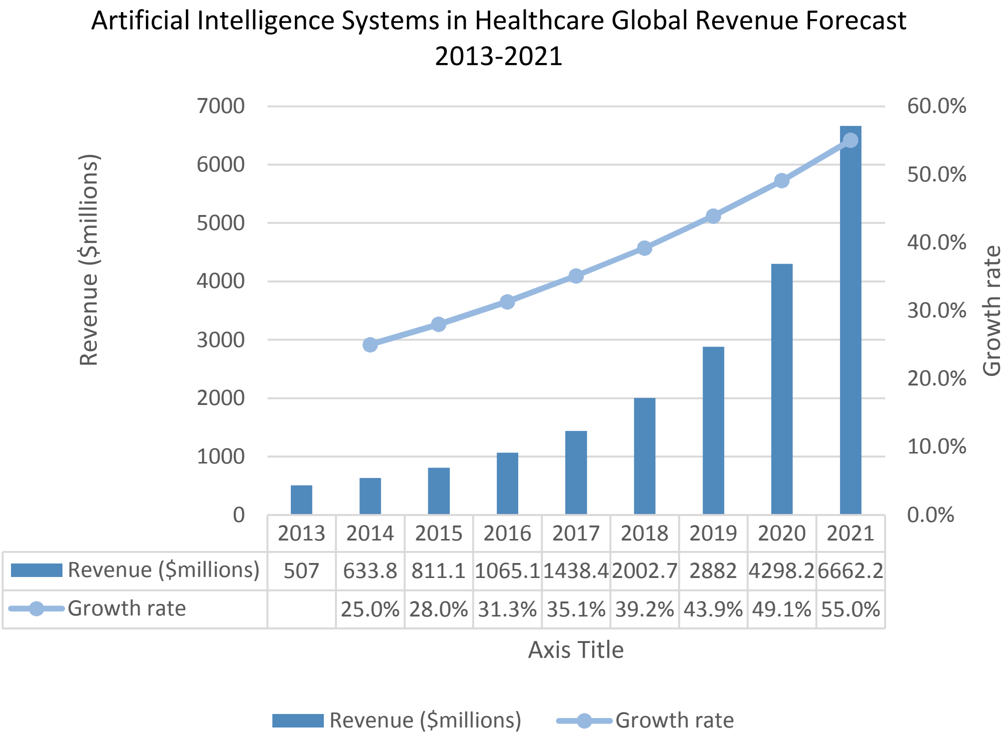
Agriculture offers vast opportunities for the application of AI solutions. These applications include drones, robotics, driverless tractors, in-field sensors for crop and soil health, automated irrigation systems, and predictive analytics, and fall mainly within the greater precision agriculture framework. Outside of precision agriculture, AI systems could find great opportunities in areas such as plant breeding, biotechnology, and agrochemical discovery.

MARKET OVERVIEW

HEALTHCARE

The healthcare market for AI is focused on patient management and care, with a key promise of the developing technology being the identification of patient-centric, data-driven tools to improve treatment regimens, hospital workflows and disease prevention.[6]

The AI healthcare market is one of the fastest growing of the AI industry applications. It is expected to grow from $663.8 million (2014) to reach $6.6 billion by 2021, at a CAGR of 40-50% (2013-2021).[7] AI in healthcare is a relatively new market, with large growth potential as the technology integrates with the healthcare sector. The market revenue forecasts and growth rate are plotted in the chart below (base year 2015).[8] Note that as a disruptive technology area, market forecast data for AI applications in healthcare vary greatly as described in the application breakdown later in this section of the report.



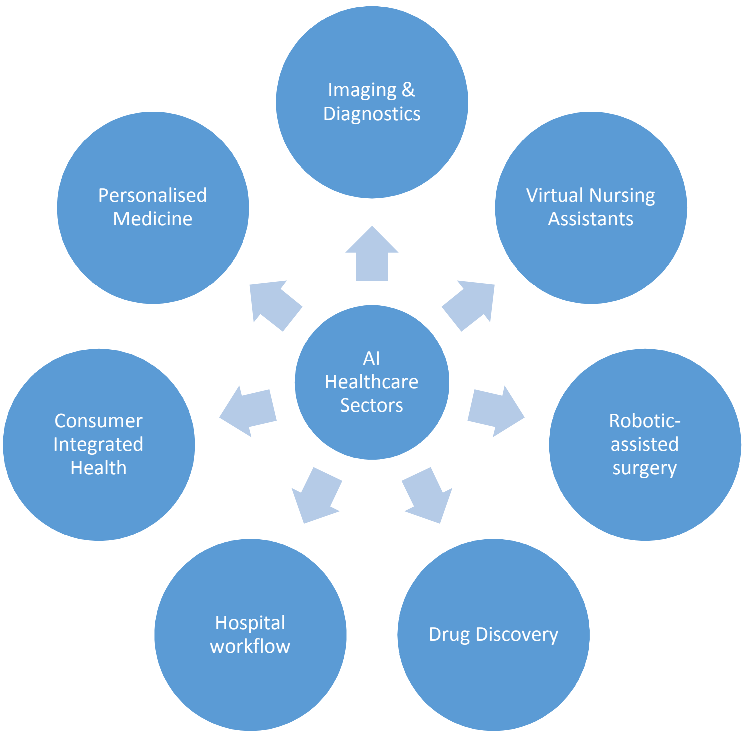
A snapshot of projected market sizes for healthcare, medical diagnostics & imaging, and drug discovery are summarised in the table given below. For healthcare as a whole, the projections are given to 2021 and for drug discovery and diagnostics & imaging to 2024.

[6] *Biotechnology Report: Beyond Borders Staying the Course*, EY (2017)
[7] *Artificial Intelligence: Healthcare's Nervous System*, Accenture (2017)
[8] *Cognitive Computing and Artificial Intelligence Systems in Healthcare*, Frost & Sullivan (2015)

Market	Value (USD)	CAGR 2016-2024
Healthcare	$6.6bn (2021)	40-50%
Diagnostics & Medical Imaging	$2.5bn (2024)	40%
Drug Discovery	$4bn (2024)	40%

AI-enabled solutions in healthcare are based on data mining of patient information, enabling that information and making treatment decisions. AI solutions for hospital workflows offer opportunities to enhance care delivery whilst bringing much-needed cost benefits. Particular areas of interest are robot-assisted surgery and diagnostics, with some estimates suggesting that AI offers the potential to improve patient outcomes by 30-40% whilst reducing treatment costs by as much as 50% in some cases.[8] The tools have the potential to alleviate workload strains on physicians and nurses across the healthcare system. AI voice-enabled symptom checkers are being developed which function to triage patients to lower-cost pharmacy or urgent care settings, directing patients to emergency departments only when emergency care is necessary. The healthcare market is harnessing AI for risk analysis, imaging and diagnostics, remote patient monitoring and virtual assistance among other applications.

The growing availability of healthcare data such as electronic health records, prescriptions and laboratory reports are the key driver of AI in the healthcare market. Combined with increasing cognitive power of computational technology to analyse and store this data, these factors are supporting the rapid growth of the market. Some of the healthcare sectors where AI is identified to be having an impact are described in the diagram below.



Sub-sectors of the healthcare market with specific AI applications and corresponding market values are given in the table below.

The top 10 near-term applications in healthcare (compiled by Accenture), were assessed on the basis of the impact, likelihood of adoption and value to the health economy. As such the figures are far larger than the market size projections summarised previously. "Value" as defined here, is the estimated annual potential benefit for the application by 2026.

Application	Value 2026 ($ billion)
Robot-assisted surgery	40
Virtual nursing assistants	20
Administrative workflow assistance	18
Fraud detection	17
Dosage error reduction	16
Connected machines	14
Clinical trial participant identifier	13
Preliminary diagnosis	5
Automated image diagnosis	3
Cybersecurity	2

Robotic-assisted surgery has the greatest value potential in harnessing AI according to the research above. Robotic-assisted surgery is already used in treatments such as hysterectomies, prostate removal surgery, bariatric surgery and hernia repair. An RBC Capital Markets survey found that U.S. surgeons expect that about 35% of operations will involve robots in five years, up from 15% in 2016.[9] Solutions are being developed using AI to integrate patient medical records with operating metrics to guide and enhance physician precision during procedures. These platforms will learn from surgical experiences to improve outcomes. Much of the activity in the sector so far is in surgical solutions for orthopaedic surgery. Value projections will increase with the development of robotic solutions for a greater diversity of surgery. An example is **Mazor Robotics** which is using AI for both minimally invasive surgical operations and more complex procedures. The tool harnesses CT scans loaded into a 3D surgical planning tool to assist surgeons in placement for spinal surgery with a robot arm guiding the instruments in precision surgery.

Virtual and remote nursing, to assess patient symptoms and deliver information or alerts to clinicians when patient care is needed, would reduce unnecessary hospital visits. These tools can learn and develop beyond patient triage, gaining expertise in patient treatment recommendations. **Sense.ly** is a virtual care AI developer working on a nurse avatar named

[9] http://fortune.com/2016/07/28/surgical-robot-development-intuitive-surgical-medtronic-google/

Molly. It is connected to physicians in real time when more detailed information is needed. It is also integrated with wired and wireless medical devices.

Hospital administrative workflow assistance tools would offer capabilities such as voice-to-text transcription for recording patient notes, prescriptions and tests. This could gradually eliminate non-patient care activities, saving work time for physicians and nurses.

Personalised medicine and genomics will enhance the personalised treatments market, supported by the growing volumes of big data in healthcare and analytics capabilities to carry out data mining and accelerate smart medicine.

TECHNOLOGY SEGMENTATION

AI is particularly useful for analysing unstructured data. Unstructured data in the healthcare industry currently is common, with clinicians having to manually complete reporting. It is estimated that over 75% of all patient information is not structured.[10] Therefore AI can be applied widely across the healthcare sector.

The data input to the machine learning technologies could come from a number of sources in the healthcare delivery system including patient electronic medical records, medical device data, diagnostic reports, medical images, laboratory reports, clinical scientific literature, social media feeds and healthcare insurance claims.

This data is then harnessed by a number of technologies which together make up AI solutions in healthcare.[11] These are summarised as follows:

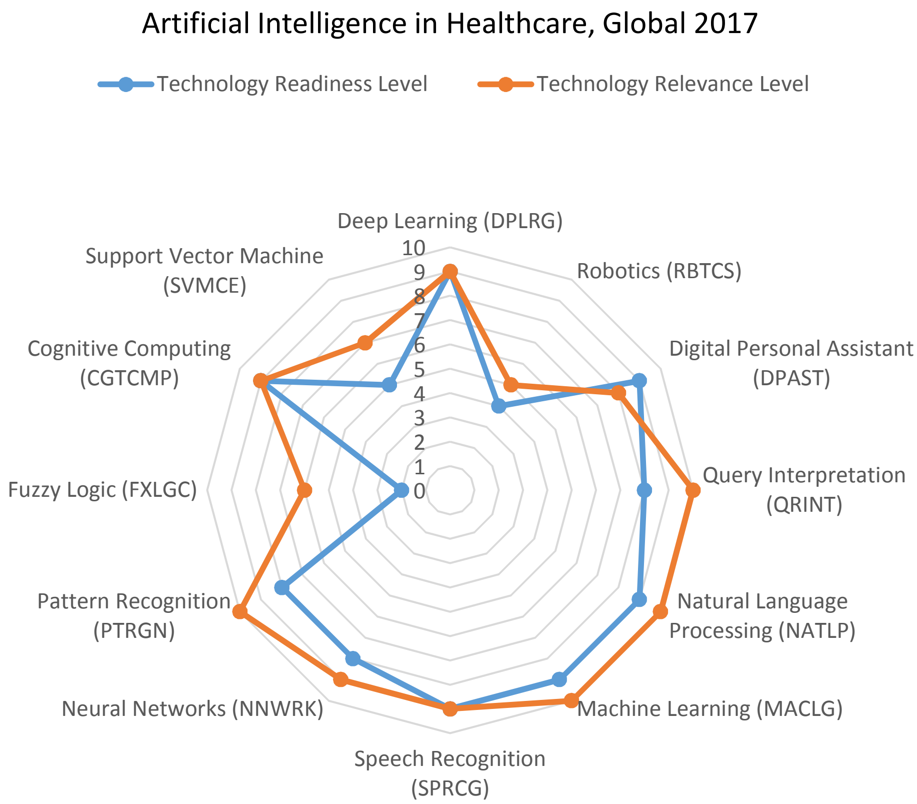
Technology platform	Description
Deep Learning	A form of machine learning in which the platform can carry out unsupervised learning via neural networks, when given certain data. Importantly, the evaluation of the information has not been programmed. Tools are being developed to process large volumes of medical data, reducing uncertainty in treatment decisions.
Robotics	Surgical robotic systems are leading the AI applications in healthcare, delivering improvements in precision and accuracy of surgical procedures, enhancing quality of care.
Personal Assistant	These solutions provide digital monitoring of patients vital statistics and alert nurses when care or changes are required.
Natural Language Processing	These systems function by converting lengthy narrative text such as clinical notes into actionable insights. The technology identifies key concepts and phrases in source material to deliver fast analysis.
Machine Learning	These systems are able to predict a pattern or analyse a trend in a dataset, which for healthcare can shape clinical outcomes. Deep learning is a form of machine learning.

[10] https://aibusiness.com/how-is-philips-improving-healthcare-through-ai/

[11] *Artificial Intelligence & Advanced Analytics in Healthcare*, Frost & Sullivan (2017)

Technology platform	Description
Image Processing	Techniques such as fuzzy-logic are allowing computer-aided diagnosis by processing large amounts of medical images in a short time to derive critical insight on disease prognosis.
Speech Recognition	These technologies leverage deep neural networks and machine learning to capture speech and language of patients and clinicians, capturing information for electronic health records.
Statistical Big Data Analysis	Predictive analytics integrate advanced computing with statistical methods to predict the outcomes of care for individual patients at speeds not achievable manually
Predictive Modelling	Involves the application of mathematical models to predict patient outcomes, including evaluating potential costs or risks associates with managing a specific patient population.

An assessment of technology readiness and technology relevance levels for the above AI platforms in the healthcare industry was conducted in 2016 market analysis by Frost & Sulivan.[11] The research has graded these in the adapted radar chart summary below:



The penetration of the AI technologies in healthcare, including medical devices & imaging, pharmaceutical & biotechnology and healthcare IT solutions are discussed in more depth throughout this report. In summary:

Medical Devices & Imaging: robotics (RBTCS), digital personal assistant (DPAST) and cognitive computing (CGCTG) technologies are thought to have the highest penetration of AI solutions in this application. Speech recognition (SPRCG) is regarded to have a medium level of penetration. Those technology basis with lower penetration include deep learning, query interpretation, natural language processing, machine learning, neural networks, pattern recognition, fuzzy logic and support vector machine. Nonetheless this analysis was conducted in 2016, and the sector is fast evolving with NLP solutions and neural networks companies and technologies emerging across the sector. In the medical imaging arena CT scans, MRI scans and picture archiving and communications (PAC) have enabled doctors to achieve 60-70% more accurate results instantaneously.[12] Emergence of novel and promising applications for disease diagnosis and monitoring is anticipated to drive artificial intelligence market growth.

Healthcare IT solutions: many of the AI technologies categorised above display high penetration in the healthcare IT solutions application to aid workflow. Those that are assumed to be further behind in development include support vector machine (SVMCE) and robotics (RBTCS). Support vector machine is a tool that analyses data used for classification and regression analysis. It uses machine learning theory to maximize predictive accuracy.

In addition to robotics for surgery and digital robotic personal nursing assistants, another increasingly important application for AI in healthcare is in clinical research. This is enhanced by the growing use of AI tools in genomics and precision medicine, which promises to further the agenda for personalised treatments. Again, big data analytics capabilities and the growing volumes of healthcare and patient data are aiding this and identifying appropriate patients for clinical trial research, which will drive better personalised medicine in patients.

DIAGNOSTICS & MEDICAL IMAGING

AI technologies in a clinical setting will strengthen the medical imaging and diagnosis processes. Frost & Sullivan reports that AI has the potential to improve outcomes by 30-40%, whilst reducing the costs of treatment by as much as 50% with much impact in the near term coming from more effective, earlier diagnosis. The market for AI in medical imaging and diagnostics is forecast to witness more than 40% growth, exceeding $2.5 billion by 2024.[12]

The pharmaceutical, biotech and healthcare industry as a whole has experienced a shift in focus to creating value in a patient-centric approach. AI technologies such as natural language processing, neural-network capability and deep learning allow unstructured data to be processed for more accurate and faster diagnosis. Key drivers for diagnostics include:

- Earlier detection of pathogenesis, recognising small shifts from baseline state in a patient – AI has the potential to detect signs of cancer in mammograms much earlier than human clinicians can.
- Earlier identification of pandemics and disease progression across populations.
- Machine learning can enable doctors to make more personalised treatment decisions based on specific patient records.

[12] https://www.gminsights.com/industry-analysis/healthcare-artificial-intelligence-market

The significant number of technologies under development and in prototype or clinical trials suggest that AI-powered diagnostics departments will feature in many future hospitals. Diagnostic centres are leveraging deep learning and pattern recognition to reduce diagnosis turnaround time, and improve pathology workflow efficiency and accuracy of diagnosis. Core AI technologies behind diagnostic and imaging platforms are based on deep learning and speech recognition.

Market analysis on the technology readiness level (TRL), patent intensity and publications for AI in diagnostic and imaging in healthcare was conducted by Frost & Sullivan.[11]

Technology	TRL	IP Publication	Academic Publications
Deep Learning	9	243,000	162,000
Speech Recognition	8	238	221,000

Cancer diagnostics and imaging are a current core focus for AI powered diagnostics, demonstrated by the start-up companies, deals and hospital partnerships emerging in the field. Radiology in particular is one area where AI solutions are being developed for analysing CT scans and X-rays to efficiently identify potentially cancerous lesions. AI in medical imaging has improved cancer tumour diagnosis at much earlier stages compared to traditional radiology.[12]

A key area of early interest is disease prediction diagnostics for far earlier stages of disease progression than is currently possible. For example, the development of computer intelligence tools which have the ability to process images taken before disease is diagnosed such as mammogram pictures, may allow quantification and identification of early pre-disease signs in complex images which current medical experts are not able to recognise. In the US AI has been used to review and translate mammograms 30 times faster with 99% accuracy.[13] This has benefits such as a reduction in the need for unnecessary biopsies and reducing the patient stress of misdiagnosis.

In the diagnostics arena, two of the most well-known players include **IBM Watson** for Health and **Google DeepMind Health**. Example diagnostic and imaging companies and partnerships include:

- Hospitals and speciality cancer centres such as the **Mayo Clinic** (US) and **Kaiser Permanente** have been adopting cognitive computing solutions such as **IBM's Watson** to diagnose cancer much earlier, with demonstrated benefits of creating a customised treatment plan for patients.
- **Infervision** and **Shanghai Changzheng Hospital** (China) are partnering to assess lung cancer patient lesions in CT scans and X-rays. **Infervision** also partners with **GE Healthcare**, **Cisco** and **Nvidia**; working across 20 tertiary grade A hospitals in China.

[13] *What doctor? Why AI and robotics will define New Health*, PWC (2017)

The technology uses CT images to learn the core characteristics of lung cancer to detect the suspected cancer features through different CT image sequences.[14]

- **Human Diagnosis Project** (US), **Human Dx**[15], is an AI platform collating medical knowledge of >6,000 doctors into a superintelligence platform to order, test or prescribe medication. It allows primary care doctors to access specialist expertise through the online platform, securing diagnosis of conditions within days rather than months of waiting for specialist appointments. The platform's natural language processing algorithms will examine keywords in each entry and direct it to specialists. The tool also aggregates the responses from specialists, and assesses them against previously stored case reports. It validates and weights each specialist's diagnosis according to confidence level. Thus the insight gained from one patient can be translated to others in future.[16] The company is partnering with seven of the top US medical institutions to scale up the platform, which relies on limited or no access to specialist medical expertise and aims to support 30 million people currently uninsured or on Medicaid.

- **Gauss Surgical**, a US-based company, has developed deep learning, pattern recognition and speech recognition to find solutions to improve the clinical testing and evaluation process and timeframes involved. Big data analytics have allowed improvements in such decision-making by analysing large datasets of clinical information to infer patterns of disease progression and diagnosis.

- **Zebra Medical Vision**, **Enlitic**, **qure.ai** and **Mckesson** are developing AI-based solutions for early diagnosis of disease, especially cancer and psychiatric disorders. These developers are harnessing deep learning, cognitive computing, machine learning and neural network algorithms to create platforms to support clinical decision making.

Over the longer term, robotic solutions to carry out diagnostics and treatment is a real possibility.

CONSUMER INTEGRATED HEALTH

The healthcare industry is experiencing increasing emphasis on preventative medicine. In parallel digital technology progression, self-tracking and wearables are developing the arena in the healthcare industry known as the *quantified self.* A key application for AI in the healthcare industry will be engagement with patients as well as pre-symptomatic, healthy individuals. Consumer wearables and similar devices are being tested in combination with AI for use in early-stage heart disease diagnostics, and detection at an earlier, more treatable stage, as well as in ongoing patient monitoring.[13]

Specific AI enhanced technologies include:

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[14] https://www.forbes.com/sites/jenniferhicks/2017/05/16/see-how-artificial-intelligence-can-improve-medical-diagnosis-and-healthcare/#148fa0506223

[15] www.humandx.org/contribute/tutorial

[16] https://www.wired.com/story/ai-that-will-crowdsource-your-next-diagnosis/

- Biometric indicators
- Prescription regimens
- Diet tracking
- Fitness tracking
- Diagnostic testing
- Mental well-being
- Genomic screening
- History and records

It is envisaged that data generated in these areas using apps and wearable technology can be captured, aggregated, stored and scrutinised with analytics technology to create tailored solutions in:

- Disease management guidance
- Wellness recommendations
- Predictive impact modelling tools
- Automated patient query support
- Cost comparison and guided buying solutions

Some example companies and a description of their platform technology is summarised in the table below.

Company	Description
Cyrcadia	The company's platform technology is a wearable vest, used to screen for early detection of breast cancer. iTBra is the company's platform technology.
CardioDiagnostics	The company has developed a device able to remotely monitor a user for heart irregularities and is used to improve cardiac monitoring and rhythm management
SkinVision	The skin cancer app uses computer vision to analyse skin lesions, it has received funding from dermatology company LEO Pharma.

It is possible that consumer and wearables data can be used for patient healthcare insurance claims in countries such as the US where healthcare support is largely driven by private insurance, as well as fundamental uses for patient care guidance and more broadly to inform government and public policies.

DRUG DISCOVERY

Drug development statistics suggest that for a drug to progress from pre-clinical research stage to approval and patient treatment the average timeframe is 12 years, with a mere 0.1% of candidates progressing to clinical trial and only 20% of these progressing to approval.[13]

The past few years has seen significant and growing interest from venture capital and pharma companies in the concept of AI. This is in the wake of the pharmaceutical industry's long-running scepticism about the promise of the technology. Estimates suggest that drug discovery held over 35% of the global artificial intelligence market share in 2016 and is anticipated to grow to $4 billion, witnessing more than 40% CAGR to 2024.[12]

The power of AI to generate significant improvements in cost, quality and clinical trial success has encouraged many pharmaceutical companies to explore AI along the R&D value chain, whether in drug discovery to address the key pain point of clinical failure rates, real-world patient outcomes or to better understand their customers.[17]

AI tools are becoming available and undergoing development for fast and efficient processes in what is known as "intelligent drug design" to:

- Recognise drug targets
- Design effective drugs
- Compound discovery
- Identify screening molecules

Given that the drug discovery process typically involves the identification of hundreds of compounds, harnessing the approaches outlined to streamline development timelines is an appealing prospect for the industry.

The approach many pharmaceutical companies are taking is to embark on partnerships with AI venture-funded start-up companies. Often sharing their own data, the pharma companies are assessing the potential of AI to identify new drug targets, new uses for existing drugs or to secure faster approval of medicines.[18]

Companies such as **Pfizer**, **Novartis** and **Merck** are advancing AI-based technologies such as deep learning and pattern recognition to reduce turnaround time involved in the process of developing new drugs. Several others are partnering with high-profile AI drug discovery start-up companies in research collaboration deals. Pharma giants such as **Sanofi**, **Takeda Pharma**, **Merck** and **AbbVie** have recently announced such partnerships.

In terms of technology penetration in the drug discovery (pharmaceutical & biotechnology) industry, the areas thought to have high penetration (2016) include deep learning (DPLRG); digital personal assistant (DPAST) and cognitive computing (CGCTG). A table summary of the penetration of the sectors described is summarised below:[11]

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[17] *AI powered drug discovery captures pharma interest*, Nature Biotechnology (2017), **35**, 7

[18] https://www.ft.com/content/a2cc8f54-bd47-11e7-9836-b25f8adaa111

PENETRATION OF AI TECHNOLOGIES

The heat map below is an analysis of the penetration of the technology sub-sectors under the AI umbrella, to broad segments within the healthcare and drug discovery industry (Frost & Sullivan). It gives an idea of how the sub-sectors are progressing in the space. For Medical Devices & Imaging for example, robotics, deep learning and cognitive computing are considered hot areas, with the use of speech recognition increasing.

Segments	**DPLRG**	**RBTCS**	**DPAST**	**QRINT**	**NATLP**	**MACLG**	**SPRCG**	**NNWRK**	**PTRGN**	**FZLGC**	**CGCTG**	**SVMCE**
Medical Devices & Imaging												
Healthcare IT Solutions												
Pharmaceutical & Biotechnology												

Key	**Description**	**Key**	**Description**
DPLRG	Deep Learning	**SPRCG**	Speech Recognition
RBTCS	Robotics	**NNWRK**	Neural Networks
DPAST	Digital Personal Assistant	**PTRGN**	Pattern Recognition
QRINT	Query Interpretation	**FZLGC**	Fuzzy Logic
NATLP	Natural Language Processing	**CGCTG**	Cognitive Computing
MACLG	Machine Learning	**SVMCE**	Support Vector Machine

Key	Penetration
	High
	Medium
	Low

GEOGRAPHICAL DISTRIBUTION

The geographical distribution of AI in the healthcare & drug discovery market is dominated by the US. In 2016 the market size was estimated at $325 million with a projected CAGR of 35% over the next 8 years,[12] suggesting a projected market of $3.5 billion by 2024. In parallel to growing big data collection and analytics, the US Federal authorities are implementing initiatives to reduce cost and improve the quality of healthcare services which is expected to drive adoption of AI across the region.

The UK is expected to drive the European healthcare AI market, with the market size expected to reach $800 million by 2024. R&D focus in the UK on genomics, as well as increasing NHS resource going towards more efficient delivery of healthcare, is expected to fuel the AI development and adoption for healthcare in the region.

China is forecast to experience the greatest growth with an anticipated 45% CAGR over the coming 6 years to 2024. Supportive government environments and drive for efficiency and democratisation of health is driving the market across all these developed regions.

AGRICULTURE

Modern Agriculture faces great challenges. The agricultural sector has grown into a highly competitive and consolidated industry. In addition, the agriculture supply chain has to contend with factors such as climate change, geographical diversity as well as economic and political factors to guarantee sustainable production.

According to the UN Food and Agricultural Organisation (FAO), the global population is set to exceed 9 billion by 2050.[19] To feed this growing population overall food production will need to increase by 70%. With available acreage estimated at just an additional 4%, it is not possible to simply plant more crops or breed more livestock. The only alternative is to intensify agriculture on its existing footprint which means doing more with less.

Agriculture needs to increase productivity and efficiency on all levels of agricultural production, while resources like land, water, energy and fertilizers are becoming more scarce and need to be managed carefully and efficiently to ensure sustainability. Experts believe that AI, within the greater framework of precision agriculture and big data, could hold the answer.

The farming industry is undergoing a so-called 'technological revolution'. With drones, robots and intelligent monitoring systems now successfully deployed in research and field trials, machine learning is becoming more mainstream and is set to revolutionise farming as the next step in precision agriculture.

The word "decision" is key in defining how AI is poised to impact agriculture. Just as AI is helping doctors and researchers make better and more informed decisions, AI has the potential to assist or fully automate certain labour activities and management decisions currently made by farmers.

In a recent study, the European Parliament recognised big data in agriculture as a way to increase productivity, food security and farmer incomes.[20] AI is not expected to replace farmers' knowledge and intuition but to complement and improve upon how decisions are made, especially as data generation, collection and analysis continues to expand. The main applications of AI and how they are expected to shape the future of agriculture are discussed in the following section.

MARKET SIZE

While AI has become a mainstay of the tech community, the agricultural field and the associated equipment and service providers have yet to vigorously pursue AI applications in agriculture.

Digital technologies and AI applications continue to penetrate agriculture – one of the least digitised industry according to McKinsey research[21] – but at a slower rate compared to other

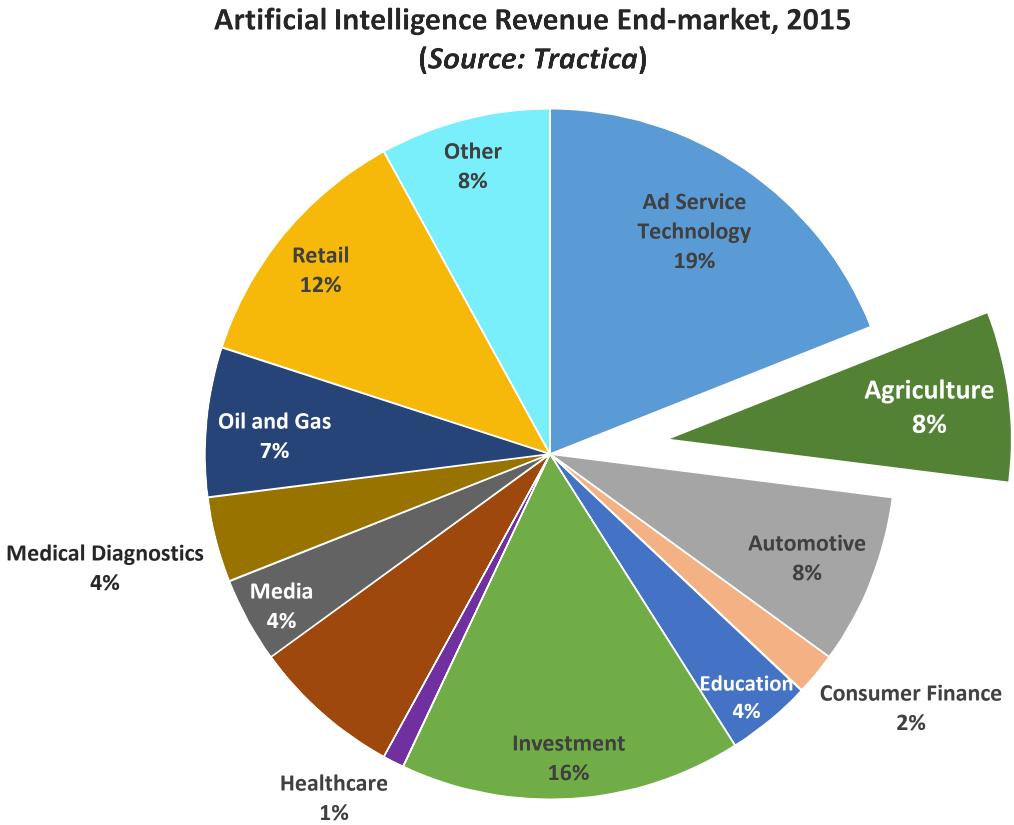
[19] http://www.fao.org/fileadmin/templates/wsfs/docs/Issues_papers/HLEF2050_Global_Agriculture.pdf

[20] *Precision agriculture and the future of farming in Europe*, European Parliament (2016)

[21] McKinsey Global Institute – Digital America: A tale of the haves and have-mores (December 2015)

sectors. This may be due to the overall lack of familiarity with AI advances or the fact that agriculture is traditionally a less tech-savvy field compared to fields such as drug discovery and healthcare.

Due to the disruptive nature of AI, forecasts for the market size of AI applications in agriculture vary widely. However, all available forecasts appear favourable and point to a strong growth for AI in agriculture in the coming years. According to BofA Merrill Lynch Thematic Investing, the total AI Revenues for 2015 stood at approximately $2.1 billion.[22] Tractica estimates that Agricultural applications account for 8% of the overall AI market[23] which means that around $168 million was spent on AI technologies for agricultural applications in 2015. Although AI applications in agriculture will continue growing, their overall market share is expected to decline as its growth will likely be outpaced by the growth in sectors such as healthcare, diagnostics and drug discovery.



The global AI market for agriculture is forecast to grow at a CAGR of approximately 23% for the next four years (from 2017 to 2021).[24] The key driving factor for the demand for AI technologies in agriculture sector is the surge in demand for agriculture robots. This growth

[22] BofA Merrill Lynch, Thematic Investing - Future Reality: Virtual, Augmented & Mixed Reality (VR, AR & MR) Primer (September 2016)

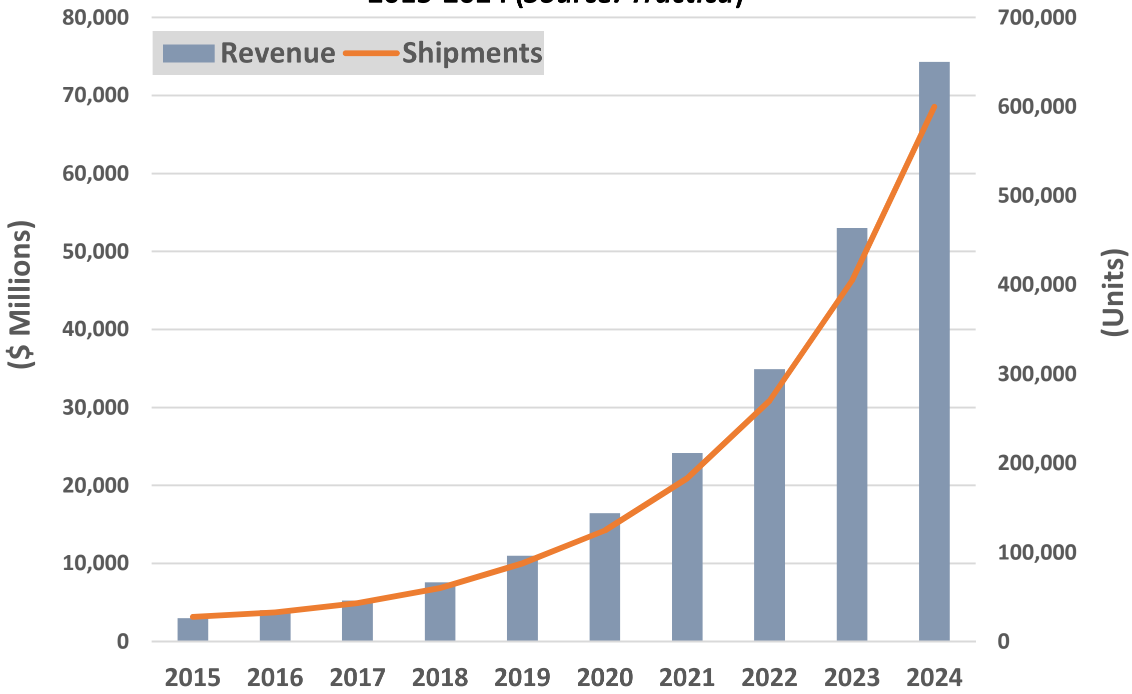
[23] https://www.lordabbett.com/en/perspectives/equityperspectives/will-artificial-intelligence-robotics-add-or-subtract-jobs.html

[24] Technavio - Global Artificial Intelligence (AI) Market in Agriculture Industry 2017-2021

in demand can be attributed to the relative reduction in agricultural workforce and the trend toward digital agriculture and new farming technologies.

According to Tractica[25], shipments of agricultural robots are expected to increase significantly in the immediate future, rising from 32,000 units in 2016 to 594,000 units in 2024, by which time the global market is expected to exceed $74 billion in annual revenue.[25]

Agricultural Robot Revenue and Shipments Trend, World Markets: 2015-2024 (*Source: Tractica*)



AI APPLICATIONS IN AGRICULTURE

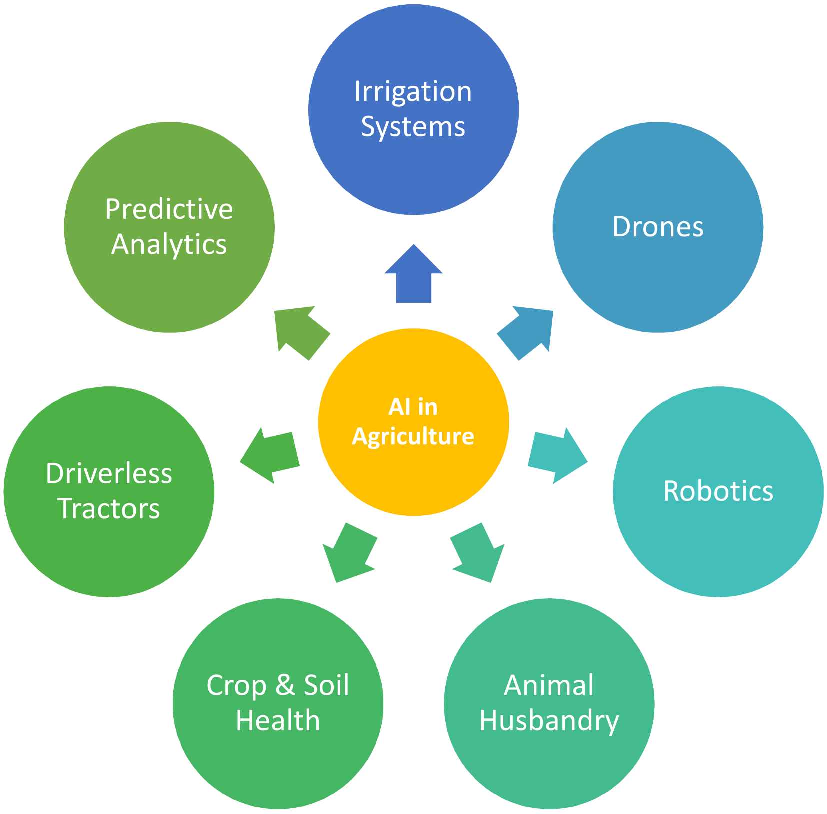
Agriculture offers numerous opportunities for the application of AI solutions. These applications will help farmers and ag-bio firms alike to better understand the natural systems in which crops grow, and allow them to use fewer chemicals and pesticides. The ultimate aim for the sector is to employ AI systems to optimise growth, tackle diseases and pathogens, and be able to monitor livestock, crop and soil conditions round the clock.

The complexity of the agricultural production asks for progress in modelling capabilities However, reliable predictions require an interdisciplinary approach and a range of technologies that include robotics, computer vision, sensors, image analysis, big data and environment interaction.

Supercomputers and AI-based algorithms are then responsible for analysing all the data gathered from in-field sensors, satellite images, drones, etc., and making decisions such as

[25] https://www.tractica.com/newsroom/press-releases/agricultural-robot-revenue-to-reach-74-1-billion-worldwide-by-2024/

when to harvest, when to irrigate and when to apply agrochemicals. At present the main AI applications in agriculture can be summarised by the figure below:



1. Automated Irrigation Systems

Traditional irrigation management is an arduous task which relies on historical weather data to predict the best utilisation of resources. Newly designed irrigation systems that rely on AI technology are fully automated and are able to measure and maintain the desired soil conditions (e.g. moisture) in real-time in order to increase yields. This reduces the need for manual labour, reduces costs and allows farmers to better manage their water supply. In addition, when sensors, machine learning and predictive analytics are brought together, smart irrigation systems are able to analyse weather conditions and predict the amount of water needed.

2. Crop Health and Soil Management

Traditional methods of soil management require the farmer to survey and test the quality of soil to plant seeds and thereafter manually carry out plantation and breeding processes. With the development of AI technology, it is easier to identify the right time for plantation or harvesting. Advanced sensors and accompanying AI technologies make the entire task much simpler for the farmer.

In a similar manner, conventional crop health monitoring methods are incredibly time-consuming and in most cases require visual inspection of the crops. Newly developed automated detection and analysis technologies – such as hyperspectral imaging and 3D laser scanning – are expected to substantially increase the precision and volume of data collected and help identify any diseases or potential infestations.

Recently, a team of researchers have developed an AI system capable of identifying diseases in the cassava plant[26] – one of the most widely grown roots globally and an important source of carbohydrates. The team used a technique known as transfer learning to teach the system how to recognise crop diseases and pest damage. The outcome was a success, as the system was able to correctly identify brown leaf spot disease with 98% accuracy. Such a system could be loaded on a smartphone, tablet or computer and allow quick identification of a disease and application of countermeasures in a timely manner.

3. Animal Husbandry

Animal husbandry, an integral branch of agriculture concerned with the care and management of the livestock, deals with all the technologies that ensure and monitor animal health, genetic qualities and behaviour. Gathering useful information and monitoring animals performance and behaviour in real-time through AI will allow farmers to manage their livestock more effectively, with less effort and minimal supervision.

Automated milking parlours is one example of an animal husbandry tool which exhibits an increasing application of AI technology. AI-enabled sensors allow the automated milking parlours to analyse milk quality and flag for any abnormalities. Furthermore, companies such as **DeLaval** and **IceRobotics,** which develop equipment and systems for milk production, animal husbandry and data collection and analysis products for monitoring cow behaviour, are expected to move towards integrating AI systems in the near future.

4. Robotics & Drones

AI robotics and drones for farming applications are seen as some of the most beneficial technologies. Robotics are the answer to the much sought-after scaling-up of farm operations and the need for automation technologies in agriculture. As farmers are automating their operations, robots and drones have become an integral part of the agriculture in improving yield and product quality.

AI forms the backbone of robotics, as it enables a machine to use language processing and deep learning capabilities to take cognitive decisions. For example, in May 2017, the start-up **Abundant Robotics** developed an apple-picking robot. In addition, more recently, **Harper Adams University** tested autonomous drones and vehicles that can be used to plant, maintain and harvest barley.

Drone technology is constantly improving, supporting new ways of increasing crop yields through in-depth field analysis, mapping of crops, long-distance crop spraying and high-efficiency crop monitoring. Practical applications are constantly evolving and are already considered invaluable by several farmers.

5. Driverless Tractors

Although technology firms have been developing adaptations of driverless vehicle technology for quite some time, the technology is not quite market-ready. Nevertheless, a combination of cutting-edge software, sensors, radars and GPS is soon expected to facilitate the transition from people-driven tractors to fully automated vehicles that will reduce

[26] Ramcharan *et. al.* (2017) *Deep Learning for Image-Based Cassava Disease Detection*, Front. Plant Sci., **8**, 1852

pressure on the existing workforce and allow for more acreage to be worked around the clock. According to Goldman Sachs, driverless tractors could significantly reduce farm labour costs and increase farmers' revenues by more than 10%.[27]

As far as agriculture is concerned, the autonomous driving trend is mainly focused on large farm machinery (i.e. tractors). In August 2017, Europe's **CNH Industrial**, known for its Case IH tractor brand, unveiled an autonomous concept tractor. The Case IH Autonomous Concept Vehicle makes use of LiDAR (light imaging, detection, and ranging), GPS, and cameras to orientate and sense stationary or moving obstacles in its path. The machine is designed to operate until its operator assigns a new path. **Deere** and **AGCO**, two rival farm machinery manufacturers, also have similar technologies and are working towards replacing farm machinery with autonomous unmanned versions. Recently Japan has also entered the race for the development of autonomous tractors with **Yanmar**, **Kubota** and **Iseki**, three different companies, leading competing robot-tractor projects.

6. Predictive Analytics

Predictive analytics focus on using machine learning algorithms to generate prediction models that can take into account parameters such as different market scenarios, yields, expected weather conditions and operational costs to maximise efficiency.

APPLICATIONS OUTSIDE OF PRECISION AGRICULTURE

While the on-farm applications of AI are certainly important, the application of AI to the discovery and development of more efficient agricultural inputs should not be neglected. Although until recently AI technologies were not tuned to analyse data from chemical and biological systems, there are many opportunities for leveraging AI in areas such as plant breeding, biotechnology, and agrochemical discovery.

In fact, AI systems may find more rapid adoption for the development of new crop varieties, livestock breeding, fertilizers, or crop protection products than for precision agriculture applications. This assumption can be supported by two factors:

- Plant and animal breeders and agrochemical developers have been meticulous about collecting and storing detailed data over the past decade. Consequently, there is a wealth of available information regarding, sequencing data, SNPs, pedigree, structure-activity relationships, toxicity and biodegradability of synthetic compounds.
- The financial gains from accelerating agricultural R&D efforts could be quite large.

As of 2016, Philips McDougall analysis estimated that bringing a new crop protection product to the market requires the analysis of over 160,000 compounds – equivalent to more than 11 years of R&D and overall costs that exceed $280 M per commercial product.[28] The industry collectively (a total of 11 companies analysed) has dedicated over $2.6 billion to

[27] https://www.cnbc.com/2016/09/16/future-of-farming-driverless-tractors-ag-robots.html

[28] *The Cost of New Agrochemical Product Discovery, Development and Registration in 1995, 2000, 2005-8 and 2010 to 2014. R&D expenditure in 2014 and expectations for 2019*, Phillips McDougall (2016)

the R&D of new agrochemicals per annum. AI systems can help speed up the process and improve efficiency.

Monsanto is one of the first big ag-bio firms to recognise the untapped capabilities of AI systems in the field of agricultural inputs. For example, Monsanto and **Atomwise**, a start-up that develops AI systems for molecular discovery, have recently formed a research collaboration to increase the speed and probability of discovering new crop protection products.[29] This collaboration is leveraging deep learning algorithms and supercomputers to analyse millions of molecules for potential crop protection products during early stage chemical discovery. Atomwise could help Monsanto reduce the time and cost of discovering new active ingredients significantly.

In addition, Monsanto has established a collaboration with **Second Genome**, a venture-backed company that relies on expertise in microbiome science to discover and develop novel healthcare products, including therapeutic candidates for inflammatory bowel and metabolic diseases. The collaboration will make use of Monsanto's extensive genomic databases and Second Genome's expertise in analysing microbial function through big data metagenomics, protein discovery, machine learning and predictive analytics to accelerate discovery of novel proteins for next-generation insect-control solutions.

The benefits of AI are also applicable to plant breeding. Monsanto estimates that the evaluation of corn hybrids in field trials prior to commercialisation can take up to 8 years.[30] Historically, a breeding program will select from a set of hundreds of thousands of varieties around 500 combinations to move on to trials, a selection constrained by the logistics and costs associated with the field trials. To address the issue, Monsanto has developed an AI algorithm, based on historic field trial and molecular market data, which can predict which hybrids will exhibit the best performance during their first year of field testing. This algorithm has helped Monsanto accelerate its breeding process and scale the size of its breeding pipeline five-fold.

In a similar manner, **Syngenta** has recently announced a partnership with the 'AI for Good Foundation' to launch the 'Syngenta AI Challenge', an international competition focused on leveraging AI tools for use in seed breeding.[31] Entrants are given access to datasets that include seed genetic information as well as soil, weather, and climate data. The ultimate goal is to develop algorithms that can determine which variety or varieties should be planted in a given area under specific conditions.

On the academic front, researchers at **Carnegie Mellon University** are working on a new initiative called FarmView which combines sensors, robotics and AI to create mobile field robots that will improve plant breeding and crop-management practices. FarmView uses AI tools to relate plant phenotype data with genetic and environmental data and help

[29] https://monsanto.com/news-releases/monsanto-and-atomwise-collaborate-to-discover-new-crop-protection-options-using-artificial-intelligence-technology/

[30] https://www.forbes.com/sites/themixingbowl/2017/09/05/can-artificial-intelligence-help-feed-the-world/#517e3daa46db

[31] https://www.prnewswire.com/news-releases/syngenta-and-ai-for-good-foundation-launch-new-ai-challenge-to-address-world-hunger-with-machine-learning-300398665.html

understand the relationships between genetics, environment, and crop performance. On the breeding side, **University College Dublin** (UCD) has been working on an algorithm that makes use of statistical analysis coupled with machine learning to predict phenotypes in crops and animals based on sequencing data, SNP data, and pedigree. UCD has recently launched a start-up around the technology called **Prolego Scientific**.[32]

PATENT INTELLIGENCE

This report focuses largely on the application of AI in the life sciences. Given the importance of IP to the industry, we have conducted a market overview analysis of how the technology is impacting patent intelligence and analytics.

The number of IP assets globally is growing. According to the WIPO there were 2.7 million patent applications made in 2015 – a 7.8% growth in patent filings on 2014. This upward trend in filings has continued for at least 20 years. Therefore, IP documentation and resources are growing. Finding relevant information in this vast amount of data is becoming more difficult. Historically, searches have been carried out manually, with static search databases being the only support tools.[33] Patent specialists have long used Boolean and positional search for patent-related discovery, combing through large amounts of literature using advanced syntaxes and manual categorization systems. The IP industry is another market where AI is at a relatively early stage but shows great promise, by improving both retrieval efficiency and accuracy. Modern searching can overcome the inherent ambiguities that confound classic keyword search by using machine learning techniques.[34]

AI and machine learning can not only automate the process of searching huge databases but also store and use previously collected data to improve the accuracy of future searches. AI can also be used to provide insight into a geographical or vertical market. For instance, insight into the strengths and weaknesses of markets in certain countries could be cross referenced with competitive IP data to deliver an instant overview of the most beneficial geographies to apply for further protection. By employing big data approaches to manage technology intelligence, companies can foster new forms of adaptive learning in innovation and strategy.

INDUSTRY APPLICATIONS

Conventional Patent Searching

Key tasks associated with machine learning techniques, integrated into commercial software for IP analysis, are clustering, classification and spatial concept maps.[35] Clustering normally comprises unsupervised methods of organizing document collections based on a similarity comparison between each member. With a fixed number of clusters identified at the outset,

[32] http://www.prolegoscientific.com/
[33] http://www.ipwatchdog.com/2017/07/27/role-artificial-intelligence-intellectual-property/id=86085/
[34] http://www.ipwatchdog.com/2017/10/07/nothing-artificial-intelligence-ai-meets-ip/id=88517/
[35] https://patinformatics.com/machine-learning-in-patent-analytics-part-1-clustering-classification-and-spatial-concept-maps-oh-my/

document collections that meet a threshold similarity component are grouped together. The two most often used algorithms in patent analysis tools are k-means, and force directed placement.

Classification, on the other hand, is usually accomplished with a supervised machine learning method that uses learning sets to identify key attributes of documents in a category. New documents are compared to the learning collections and assigned to a class based on their similarity to the documents that have already been assigned to the category. Two frequently applied classification models are artificial neural networks, and support vector machines.[36]

As applied to patent analytics, the most frequently used sources of content, for both clustering and classification exercises, come from patent classification codes, and raw or standardised text, from a source document.

Spatial concept mapping generally begins with clustering or classification methods, but adds an extra component – identification of relative similarity between the categories created to the task. The tools involved arrange the document clusters or classes in two-dimensional space by considering the similarity of the documents, or clusters, relative to one another, over the entire collection.3 Clustering methods create mathematical representations of the documents, which are then organised into clusters and visualized into "maps" that can be interrogated for analysis. One of the most well-known classification-based methods is the Kohonen Self Organizing Map – a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretised representation of the input space of the training samples, called a map.[36]

A pioneering method in spatial concept mapping is the ThemeScape[37] tool, which accesses titles and abstracts, claims, and/or the full-text of patent documents, as well as various fields in the Derwent World Patent Index (DWPI). A particularly powerful combination is the use of the Advantage, Novelty and Use fields of the documents of interest. These fields highlight key aspects of the inventions associated with the patents, and generally produce maps that highlight the differences, and uses of the corresponding technology.[38]

Next-Generation Patent Searching

Existing solutions fail to take into account that companies often use different words to describe similar inventions. This makes search efforts based on the similarities between words prone to miss relevant prior art. Additionally, existing techniques do not account for temporal changes in the terminology used to describe particular inventions. This is not a trivial omission as, by definition, the search for prior-art requires comparing an invention with others produced at different points in time.[39] In the past decade, natural language processing (NLP) systems have been applied to searching patents, and a variety of information retrieval systems that incorporate written text have made appearances in the patent space.

[36] https://patinformatics.com/machine-learning-in-patent-analytics-part-2-binary-classification-for-prioritizing-search-results/

[37] https://clarivate.com/products/derwent-innovation/

[38] https://patinformatics.com/machine-learning-in-patent-analytics-part-3-spatial-concept-maps-for-exploring-large-domains/

[39] https://patinformatics.com/ai-patents-applying-machine-intelligence-to-patent-searching/

The European Patent Office's "Smart Search" tool already uses AI to guess the patent field in which to search,[40] while the Japan Patent Office plans to begin using artificial intelligence technology in 2018 to process patent, trademark and design applications. It will apply pattern analysis and recognition software to a number of due diligence tasks where ample documentation exists to "train" the software.[41]

Companies such as **IP.com** and **AI Patents** have developed AI-enhanced semantic searches, enabling the use of ordinary language to retrieve documents containing similar concepts or meanings. Here, a deep belief neural network extracts ("learns") concepts and meanings from patent and related literature using algorithms which encode core document concepts and queries into highly comparable semantic mathematical vectors that help to "see through" limitations of language.[34]

Meaning is discovered through statistical analysis of word patterns and distributions natively occurring in massive collections of patent documents. Neural network machine learning systems analyse the large-scale probability and distributional properties of words in document collections. The derivation of meaning from these patterns is well supported in the technical literature and is referred to as the "distributional hypothesis of meaning." The Distributional Hypothesis refers to words with similar distributional properties having similar meanings. This statistical approach currently dominates the field of NLP and there is an enormous literature on it as well as rapidly advancing practical applications from the biggest technology companies in the world including **Google, Apple, Facebook** and **Amazon**.[42]

The most advanced intellectual property and patent search tools are powered by more than just neural network analysis and the resulting semantic vectors. They also build a language model and a knowledge graph of the literature — and use a smart combination of these technologies to provide accurate results. Technology like this is the next generation engine for today's Boolean/positional searchers. Deep learning and neural networks, combined with statistical models, are the next steps to applying AI to patent searching. Deep learning AI discovers contextual relationships between words. It captures "o-nyms" – synonyms and more – that can expand or narrow the scope of search.

These "similar" words are a roadmap to a more precise, semantically relevant search that delivers more complete, useful results with less "noise" and fewer false positives.

KEY PLAYERS

Companies using AI for patent intelligence are outlined below. Most are small, specialist organisations providing a patent searching platform based around AI-enhanced semantic searches. Many are recently-established platforms, or are still in the product development stages, but are developing next-generation searching capability for this emerging market.

[40] Hitchcock, D. (2017) *Patent searching made easy: how to do patent searches online and in the library*. Berkely, CA: Nolo

[41] https://asia.nikkei.com/Politics-Economy/Policy-Politics/Japan-looks-to-AI-to-simplify-patent-screening

[42] http://ip.com/why-ipdotcom/semantic-search/

AI PATENTS

AI Patents (Durham, NC) has developed a conceptual, free-form search engine that addresses the challenge that the same idea can be described in multiple ways, developing a search process that “learns” from thousands of patent examination decisions. These decisions determine that two distinct inventions describe the same scientific idea, even though their exact wording differs.

Based on this learning algorithm, AI Patents allows its users to compare patent documents based on their underlying scientific ideas, and not merely based on their textual overlap. For example, when users input a keyword into their search query, they are offered additional keywords or acronyms which other inventors have used in the past when describing identical ideas.

AMBERCITE

Ambercite Ai (Melbourne, Australia) has been developed to apply AI to patent searching using one (or more) starting patents to find a ranked list of similar patents using unique algorithms. Using a patent number, similarity analysis is performed based on a sophisticated analysis of the forward and backward citations around this patent, and the forward and backward citations to these citations, and so on. Because each citation link is an expert opinion that two patents are similar, by analysing a whole group of these opinions, and effectively combining these opinions, a 'super opinion' is built of the most similar patents to the starting patent, which can then also be filtered by keyword.

IP.COM

IP.com is based in Fairport, New York. Its InnovationQ software is powered by a patented neural network machine learning technology – known as Semantic Gist – which allows it to understand the meaning of documents and queries. This system allows it to match queries to documents based on meaning rather than keywords. This can deliver superior precision and recall because meaning or concept matching overcomes the inherent ambiguities in ordinary language, especially synonymy and polysemy. InnovationQ understands that two terms — "vehicle" and "car"—have similar meanings (synonymy) while a single term like "stream" may have multiple unrelated meanings (polysemy).

As a document collection grows over time, new terms and concepts inevitably emerge while others may shift in meaning. For example, phrases like "internet of things," and "deep learning" have gained currency in the technical literature in recent years. The same is true for individual words like "multicore" or "qubit". Semantic Gist automatically adjusts to these changes in the topical composition of the document collection. It detects this "semantic drift" through its learning algorithm and re-weights concepts and topics accordingly. This makes the system self-evolving and allows it to sustain high precision and recall in the retrieval task as the balance of topics and concepts in a document collection changes.10

DERWENT INNOVATION

Derwent Innovation is the search and analytics platform of Clarivate Analytics (Philadelphia, PA), providing access to global patent data and scientific literature. It uses machine learning and modern big data engineering practices to produce new predictive data on the legal status and expiration date for every patent record in its collection from the DWPI. Having a clear understanding of the remaining life and breadth of IP is important for determining freedom to operate, licensing scope and duration, royalty calculations, acquisition due diligence, and portfolio valuation.

Many factors influence the calculations for Estimated Expiration Date and Estimated Remaining Life. These include earliest effective filing date, National and PCT filing procedures, fee payments (or lack thereof), patent term extensions (e.g. SPCs and similar extensions for pharmaceuticals and agrochemicals). For the United States, other factors such as the 1995 Rule, terminal disclaimers, and patent term extension and adjustment are taken into consideration.

ELEMENTARY IP

Elementary IP (San Francsico, CA) is a patent analytics platform which uses deep learning AI to generate word graphs for more precise searches. It uses proprietary topological clustering to extract the key elements of invention in a patent document. These elements of invention are then used as queries for similar document search, yielding better precision. The search results are quite sensitive to the query terms, and appear to work best for an optimal set of invention elements, which may be interpreted as the document's "search passphrase" to unlock the best matches clustered near the top. The user can iteratively refine the automatically discovered invention elements to optimize the "passphrase."

X-R.AI

X-r.ai are a new (2017) patent prior art search tool, powered by deep AI to make patent prior art searching faster and more thorough. Currently under development, it has a particular focus on helping make patent prosecution, licensing, and litigation faster and more effective for technology companies, and to shut down “patent trolls”. The company is based in Portland, Oregon.

PATANALYSE

PatAnalyse is an integrated technology consultancy, based in Cambridge, UK, specialising in patent searching and comprehensive analysis of the trends presented in the patent portfolio. The company uses a proprietary search management system to capture expert judgements and combine these with artificial intelligence algorithms to produce a pre-analysed universe of data tailored to each client’s needs.

The methodology is based on a pattern recognition algorithm which the company claims can find an additional 30% of ‘hidden’ patents: those which have been assigned incorrect or misleading codes by European or US patent offices. The company also uses a self-learning iteration process to improve the reliability of patent searches – for this software PatAnalyse has a patent pending.

CLEARACCESSIP

In May 2017, **ClearAccessIP** (San Francsico, CA) launched a neural network patent search as a feature of IPDealRoom – its structured diligence tool for organising and structuring an IP portfolio around the market for goods and services. The first neural network product is “IP Map”, which uses machine learning to read the contents of a portfolio, along with any attached patent records and invention disclosures. This then enables weekly updates of the IP Map, which viewers with access to the IPDealRoom can link to at any time to view a list of the most closely related disclosures to the IPDealRoom portfolio.

INNOGRAPHY

Innography (subsidiary of **CPA Global Limited**) is an analysis software platform based in Austin, Texas, that offers tools to companies managing intellectual property. Innography's primary job is using big data machine learning approaches to turn data from over 200 sources into usable, verified, update-to-date quality data. To do that, a weekly ETL (extract, transform, load) process, downloads, cleans, normalises and correlates patent and related data to make it usable by Innography's tools and software.

DOLCERA

Dolcera is one of world's largest patent analytics companies and is based in California. Dolcera PCS is a machine learning-driven platform designed to perform instantaneous patent searches. NLP and machine learning algorithms search multiple data sources beyond patent literature to generate wider analysis categories.

TEQMINE

Teqmine Analytics was founded in 2013 and is based in Helsinki, Finland. The company specialises in large-scale IP, patent, and science/technology analysis by developing databases and machine-learning data mining technologies. Teqmine's discovery capabilities are based on complex probability models built on detailed analysis of millions of full-text patents. It deploys advanced NLP and machine learning data mining algorithms with an almost unlimited processing volume, obtaining raw patent data (USPTO/EPO/PCT) directly from issuing offices and re-packaging it for optimal data mining.

Teqmine services are based on two Big Data innovations: patent similarity and technology mapping. Patent Similarity is based on complex probability models, which use detailed analysis and classification of millions of full-text patent descriptions. AI is used to discover contextual similarities, and find all potentially relevant patents. Algorithms match millions of full-text patents to the patent in question and calculate a similarity index that quantifies potentially infringing patents. Teqmine's technology map combines a mix of cutting-edge Big Data techniques, augmenting traditional cognitive IP and technology mapping processes with powerful statistical, visual and on-line tools.

MARKET DRIVERS AND TRENDS

The recent proliferation of machine learning text analysis methods is changing the status of traditional patent data analysis methods and approaches. The key market driver is the added value which more effective, more efficient analytics can bring to companies. In particular a key opportunity comes from the insight that AI can provide into otherwise impenetrable and inaccessible volumes of data.

AI, which is highly adept at processing large sets of data quickly and accurately, can help both efficiency and accuracy. This also enables law firms and IP professionals to take on a more strategic role within the organisation, generating insight from data to help shape future company performance, whilst leaving the more mundane aspects of IP management to computers.

Many IP professionals are engaged in analysing the value of their patent portfolio in terms of the most effective patents, delivering the highest licencing revenues and in which sectors/countries. By analysing large sets of data, AI is able to indicate where a company's portfolio of IP is strongest and weakest. This can, in turn shape future investment decisions in research and development, help companies understand their relative strengths and weaknesses in terms of their competitors, and enable companies to understand more about the potential opportunities in new markets.[33]

BARRIERS TO ENTRY

Machine learning opens the possibility for cost-effective analysis of full text patent data, which can mitigate the limitations of de facto standard metadata-based approaches, such as the subjectiveness of the patent classification process. By employing big data and machine learning approaches to manage technology intelligence, companies can foster new forms of adaptive learning in innovation and strategy. However, such approaches require the augmentation of human judgement in the categorisation and analysis of knowledge with machine learning methods, prompting serious challenges to the existing corporate foresight traditions. Leveraging these efforts within companies requires their systematic integration to existing strategic foresight processes.[43]

DEALS

Partnerships across industry, academia, hospitals and funding organisations are driving the development of AI in the sectors discussed in this report. A combination of internet-based searching and deal information from databases such as Beauhurst and CB Insights (CBI) has been used to collate information on collaborations, licensing agreements, venture funding and acquisitions in the life sciences sector based on AI technology.

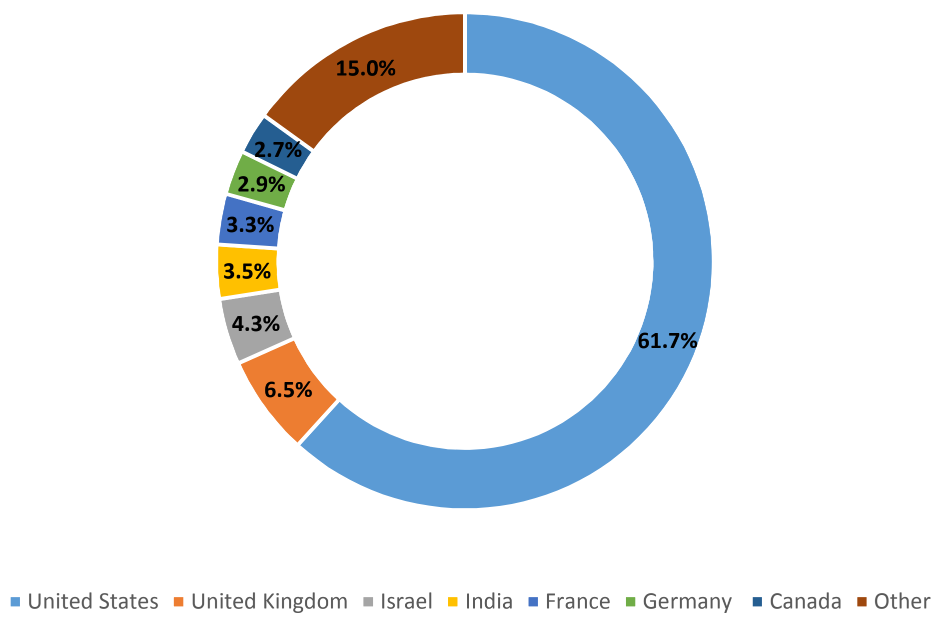
Tracking deals for the overall AI landscape across all industries, CB Insights data suggests that during 2016 there were a total of 658 financing deals globally in AI companies, with a total of $5.02 billion invested (up from $3.1 billion in 2015). In terms of geographical breakdown, deal activity is predominantly occurring in the US (61.7%), followed by the UK at (6.9%). Notably China is not included in this dataset, however, figures suggest the country is an active funder of AI research and companies, such as **iCarbonX** which received over $150m in 2017.

The breakdown of countries and the proportional deal activity occurring throughout 2016 for each region is summarised in the chart below.[44]

[43] Suominen et. al. (2017) *Firms' knowledge profiles: Mapping patent data with unsupervised learning*. Technological Forecasting & Social Change, **115**, 131-142

[44] https://www.cbinsights.com/research/artificial-intelligence-startup-funding/

AI Deal share by Geographical Region (%)



There have been a large number of venture deals, which have been further categorised by industry sector, technology area and year of completion below. Whilst the list is not comprehensive, and focuses predominantly on deals in 2016 and 2017, it provides an overview of activity and the nature and size of typical deals. Details of the identified deals are listed in Appendix 1.

HEALTHCARE & DRUG DISCOVERY

One of the top growing industries for AI venture deal-making is healthcare – in 2015, 15% of all AI venture deals were in the healthcare sector (60 deals in total),[45] with more recent data suggesting the trend is upward with over 70 deals in 2016.[46] The deals made with healthcare-focused start-ups have increased from less than 20 in 2012 to 88 in 2016.[47] According to CB Insights, more than 100 companies have raised equity funding in various rounds since January 2013. The global financing trend for AI healthcare deals is described in the chart below. The data include drug discovery-based companies.[48] Note that the data for November and December 2017 are not included – the figure given is an estimate for the year (e).

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[45] https://www.cbinsights.com/research/artificial-intelligence-healthcare-startups-funding-trends/

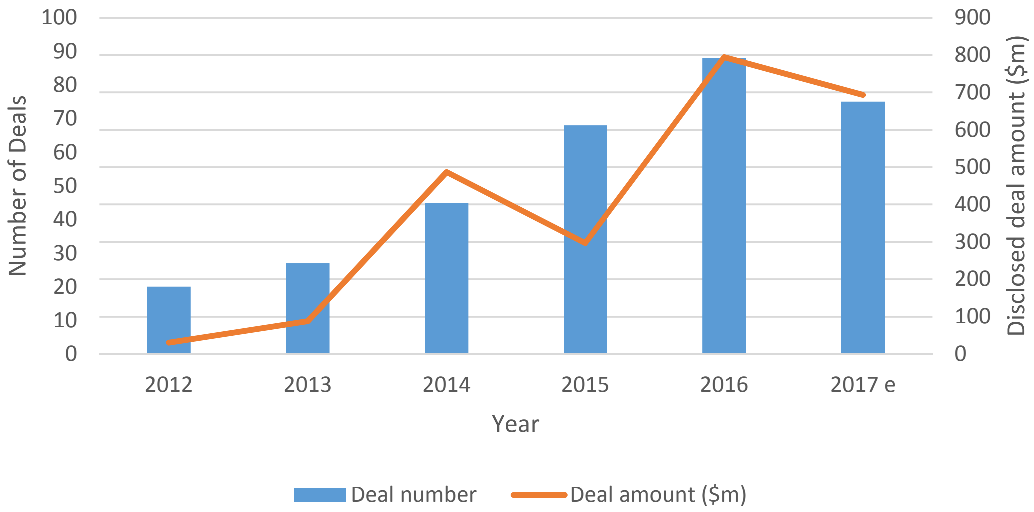
[46] *AI, Healthcare & the future of drug pricing*, CB Insights (2017)

[47] https://app.cbinsights.com/research/ai-healthcare-startups-market-map-expert-research

[48] https://www.cbinsights.com/research/artificial-intelligence-healthcare-deals-funding-investors/

GLOBAL DEAL ACTIVITY

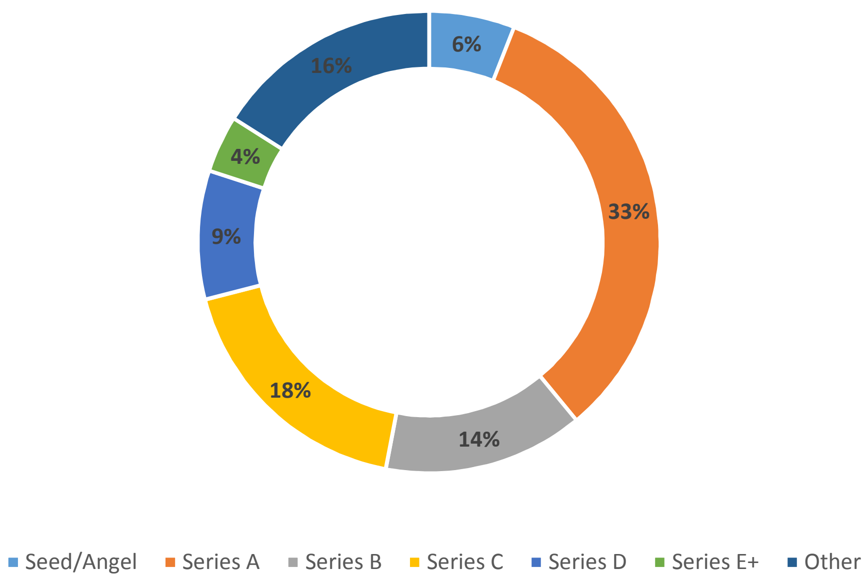
Healthcare AI Global Financing 2012-2017



The 2016 record deal amount can be attributable largely to two AI unicorn venture deals secured by **iCarbonX** and **Flatiron**. China-based **iCarbonX** is focused on developing an AI platform to facilitate precision medicine, nutrition, preventative care and disease treatment. The core focus of the company is on solutions for personalised medicine. **Flatiron** is an oncology focused AI development company with solutions such as **OncologyCloud** integrating patient data with cancer care for web-based solutions.

The split of deal share in USD for AI healthcare start-ups across the different stages of funding are summarised in the chart below (source: CB Insights).

AI in Healthcare: Deal share by USD (%) 2011-2016



Multinational healthcare and pharmaceutical companies are increasingly partnering with smaller AI biotech companies and start-ups to develop AI solutions. These partnerships are a source of some significant deals in the sector, whether through corporate venture financing or research collaborations. For example, **Johnson & Johnson** has embarked on a joint venture with **Verily** (**Alphabet** company) to form **Verb Surgical**, similarly **IBM Watson** and **Google DeepMind Health** are partnering with a number of hospitals and research institutes.

The most well-established and well-known machine-learning model for drug discovery and healthcare is **IBM Watson**. **IBM** has carried out a number of venture deals and research collaboration deals in the sector. For example, the company executed a deal in December 2016 with **Pfizer** to support the company's immunoncology drug discovery pipeline. This is representative of a number of deals with the pharmaceutical industry as well as other healthcare companies and academic institutions.

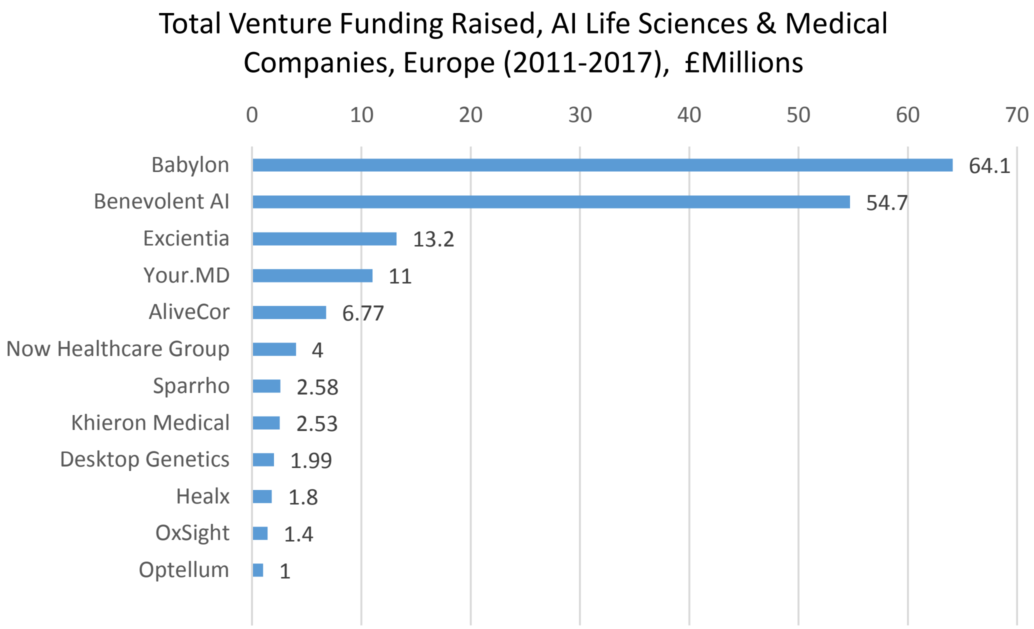
Public-private partnership alliances are also common in AI healthcare development solutions: **Google DeepMind** has multiple partnerships with NHS research hospitals; the Japanese Government has entered into alliances in the AI space to streamline development of novel drugs to boost the nation's competitive advantage in the sector; and a US company, **ATE**, is partnering with a number of companies and academic institutes for drug candidate development. In the partnership space with hospitals and care providers, there are a large number of deals at around $500k to $1 million for hospitals to use AI-related products on a trial basis. However, there are fewer deals reaching $5-$10 million.[49] These figures provide some indication that the market in hospitals is still emerging.

EUROPEAN DEAL ACTIVITY

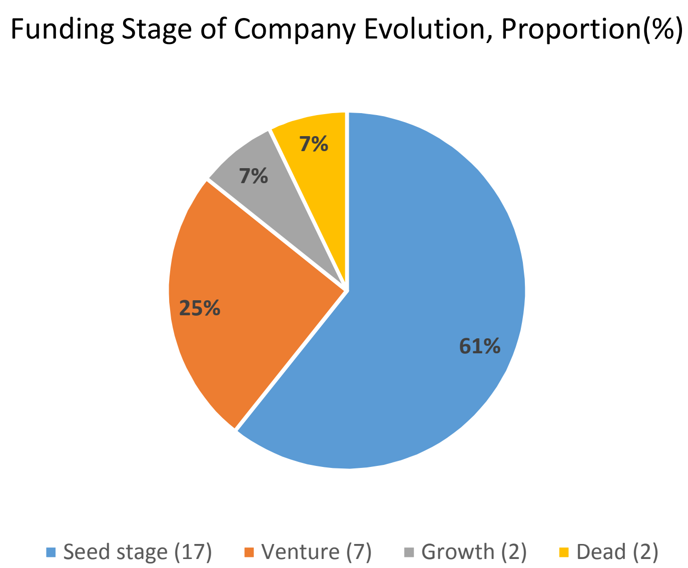
A European database tracking funding deals for early stage companies, Beauhurst, has compiled data on AI-based companies and venture deal funding over the past five years. A search was carried out, narrowing this broad dataset to companies just active across Life Sciences, Pharmaceuticals, Research Tools, Medical Technology, namely: clinical diagnostics, medical devices, medical instrumentation; personal healthcare services; nursing and care services; other personal healthcare services. The search identified 26 relevant companies, raising a total of £168 million with an average company post-money valuation of £35 million.

The following graphs illustrate the top funded companies in the dataset, including **Benevolent AI** and **Excientia** – both drug discovery companies – and **Babylon Health**, a virtual nursing patient-triaging AI company.

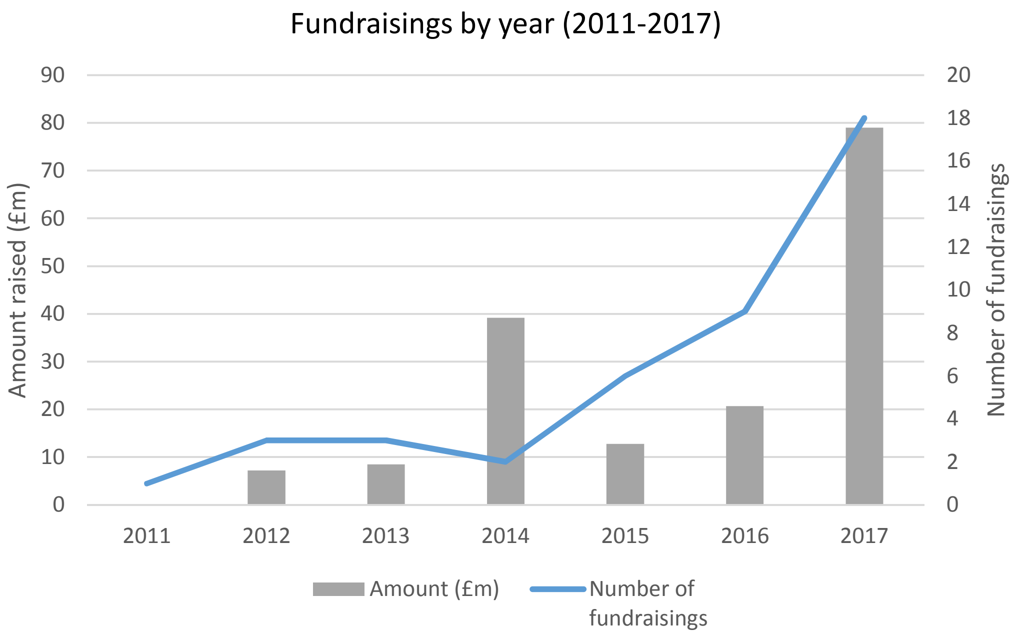
[49] https://www.xconomy.com/boston/2017/06/26/ge-ibm-race-to-deliver-on-a-i-hype-in-healthcare/



The companies are categorised as seed-stage, venture-stage, or growth-stage based on proprietary research and criteria conducted by Beauhurst. Those which are now regarded as dead, or not trading or developing, are also marked. The chart below summarises the companies, the largest proportion of which are in the seed stage of development.



In terms of the fundraising trend, the number of fundraisings recorded and the amounts raised in this set of European deals has experienced a sharp upward trend between 2016-2017, as shown on the chart below. The large 2014 figure of £39.2 million was generated almost entirely by **Benevolent AI**, which raised £39.1 million.



AGRICULTURE

Agritech firms have been experimenting a lot with AI and its potential applications in agriculture as part of the bigger Precision Agriculture concept. Deals with start-ups that focus on robotics and machine learning with applications in agriculture started gaining momentum in 2014.

According to CB Insights, Agritech start-ups have raised over $800 million during the past five years (2012 to 2017) to introduce novel solutions that will help the agricultural industry produce more on less land. Out of that $800 million more than $500 million was raised by AI-related agritech start-ups, with technologies ranging from analysing satellite images to identifying healthy strains of plant microbiome, to bring AI solutions and robotics to agriculture.

VC firms like **Bessemer Venture Partners, Accel Partners, Khosla Ventures, Lux Capital**, and **Data Collective** have been investing on robotics, drone, and computer vision companies with a focus on agricultural applications. Furthermore, big ag-bio corporations such as **Monsanto** and **Syngenta** have invested in AI start-ups with applications in agriculture. Characteristic examples of such companies include **Abundant Robotics, DJI Innovations** and **Orbital Insight**, as well as start-ups like **Blue River Technology** (please see below for more information).

The table below summarises the agritech start-ups with AI-enabled technologies that are poised to transform agricultural practices. Although the table is not exhaustive, it provides an overview of the most important start-ups active in this niche field.

Company	Category	Total Funding ($M)
Abundant Robotics	Agricultural robots	10.00
Agri Eye	In-field monitoring	0.15
Airwood Aerostructures	In-field monitoring	-
Benson Hill Biosystems	Crop/soil health analysis	34.21
Blue River Technology	Agricultural robots	30.75
Clearpath Robotics	Agricultural robots	40.79
DJI Innovations	In-field monitoring	105.00
Descartes Labs	Satellite image analysis	8.38
FarmShots	Satellite image analysis	1.77
Farmbot	Agricultural Robots	0.07
Gamaya	In-field monitoring	3.72
GeoVisual Analytics	Predictive Analytics	1.27
HUVRData	In-field monitoring	2.00
Harvest CROO	Agricultural Robots	1.71
HoneyComb Corp.	In-field monitoring	0.46
Indigo Agriculture	Crop/soil health analysis	163.50
OmniEarth	Satellite image analysis	5.16
Optimal	Predictive Analytics	0.01
Orbital Insight	Satellite image analysis	78.70
PEAT	Crop/soil health analysis	0.06
Precision Hawk	In-field monitoring	29.00
Prospera	In-field monitoring	7.00
Raptor Maps	In-field monitoring	0.72
Resson	In-field monitoring	14.00
Sensurion	In-field monitoring	2.00
SkySquirrel Technologies	In-field monitoring	1.02
Trace Genomics	Crop/soil health analysis	4.12
aWhere	Predictive analytics	12.45
ec2ec	Predictive analytics	1.06

As demonstrated by the table above, most of the agritech start-ups attracting funding revolve around four key categories:

- In-field monitoring
- Assessing crop and soil health
- Agricultural robots
- Predictive analytics

Satellite image analysis utilises mainly machine learning and computer vision technology to categorise and analyse millions of satellite images and geo-spatial data that can analyse the impact of weather changes on agriculture and provide information on crop distribution patterns worldwide.

In addition to the deals listed in the above table, **Climate Corporation**, a digital agriculture company that leverages machine learning to predict the weather and other essential elements for agribusiness to determine potential yield-limiting factors, was acquired for $930 million by **Monsanto** in 2013. In a similar manner, **Blue River Technology**, a Monsanto Growth Ventures Company, is a pioneer in designing and integrating computer vision and machine learning that enables growers to reduce the use of herbicides by spraying only where weeds are present. The technology can reduce herbicide usage up to 90% and significantly decrease costs for farmers. The firm is now looking into expanding their product portfolio. Their success has been recognised by **Deere & Company** who have recently acquired the firm for $305 million.

Abundant Robotics is a Stanford Research Institute spin-out that develops robotic systems for fruit harvesting (e.g. picking apples) and a good example of pioneering work in the field of robotics. Their technology employs the latest form of computer vision. Successful commercial deployment of their robots will pave the way for more robots in the field of agriculture and will help automate some of the most time consuming and labour intensive tasks in agriculture.

DJI Innovations, is another example of a firm whose technology will help farmers save time. DJI's drone series are able to collect data, and generate maps that identify signs of stress or disease in crops, replacing the traditional, labour intensive method of investigating crops manually. DJI has collected a total of $105 million in funding for its technology platform and serves as a good indication of how important in-field monitoring capabilities are expected to become in the near future.

Furthermore, technology firms in the field of predictive analytics have been attracting increasing attention with **ec2ec** securing over $1 million of funding in 2017 and raised over $12 million in funding (from **AgFunder**, **Aravaipa Ventures**, and **Elixir Capital**) in 2014-2015.

While the growing number of connected devices represents a big opportunity for the increasing number of agri-tech players, it also adds more complexity for farmers. In addition, the majority of farms lack the necessary information technology infrastructure, connectivity, and data storage. Despite the increasing number of new players in this niche field, the on-farm data infrastructure will need to be upgraded significantly and become more robust before AI solutions can be successfully deployed in agriculture.

KEY PLAYERS

Developments in the overall AI technologies market is led by digital corporate giants such as **Google, IBM, Yahoo, Intel, Apple** and **Salesforce**. Industry-specific companies like **Ford, Samsung, GE** and **Uber** are also emerging as AI developers in their own sectors, with transport and retail dominating in terms of technology uptake.[50]

The key players developing proprietary cognitive AI solutions for the life sciences, or harnessing AI solutions for life science applications, were identified using information from subscription databases, press articles, internet-based searching and academic literature. The landscape is comprised predominantly of start-up companies developing AI technology for healthcare, drug discovery and agriculture. In parallel, leading technology companies such as **IBM** and **Google** are working on the development of AI technology broadly, but have a sector focus on healthcare, drug discovery or agriculture in addition to the broader promise of AI across all industries.

IBM is the pioneering AI technology platform for the whole AI sector, and is a healthcare market leader with **IBM Watson** and their cognitive health business. The company has been aggressively acquiring healthcare computing companies with a focused strategy to build up their capabilities in AI, and have spent approximately $4 billion in the two years to June 2017 on acquisitions.[49]

Google/Alphabet is the most active acquirers of AI start-ups, having bought 12 companies since 2012, one of which was London-based **DeepMind** from which **Google DeepMind** has emerged. The company's life sciences division, **Verily**, has a number of projects in the AI healthcare space including a retinal imaging project in partnership with **Nikon** and a joint venture with **Johnson & Johnson** and **Verb Surgical** in the arena of robotic surgery. Indeed, the robotic-assisted surgery market is undergoing some dynamic changes. Currently the market is dominated by **Intuitive Surgical**, the manufacturer of the da Vinci Surgical System, which was launched in 2000 and commonly used for laparoscopic procedures such as hysterectomies and prostatectomies. However, an increasing number of strategic partnerships taking place between established medical device players and start-up companies in order to advance the introduction and adoption of AI-based novel surgical systems is underway. In December 2015, **Johnson & Johnson** announced its partnership with **Verily**, resulting in the formation of **Verb Surgical**. In May 2016, **Medtronic** entered into a strategic agreement with **Mazor Robotics**, an Israel-based company specialising in robotic guidance systems for spine surgery. Such partnerships highlight the investments being made to drive the growth of the surgical robotics market and help develop products for broader surgical applications.

Companies such as **GE** are also targeting a leading position in AI in healthcare. In 2017 the Boston-based company's healthcare business announced partnerships with three high-profile medical care and research institutions to co-develop AI: **UC San Francisco**'s Centre for Digital Health Innovation, **Boston Children's Hospital**, and most recently **Partners HealthCare** in the US.

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[50] *The Race For AI: Google, Baidu, intel, Apple in a rush to grab artificial intelligence start-ups*, CB Insights (2017)

Medical device companies such as **Medtronic**, **Philips** and **Siemens** are players in the sector, with a broad focus on robotic surgery, population health management, virtual nursing, personalised medicine and imaging & diagnostics. Whilst **Amazon** has not made a direct inroad to healthcare AI as yet, their virtual agent, Alexa, is being incorporated into healthcare apps by external developers and doctors who are using the tool for administrative work; as such **Amazon** may become a more significant market player in future.[49]

The slower adopters have been the well-established, multinational big pharma companies, which are starting to accept the potential of AI technology and establishing a number of partnerships, joint ventures or research collaboration deals in the drug discovery and healthcare space, such as the example of **Johnson & Johnson** discussed above.

The AI in agriculture is also quite fragmented. There is a wide range of different start-ups involved in the development and deployment of new AI powered solutions. However, some do stand out based on the amount of funding they have attracted, the nature of the technology developed and the strength of ties with some of the ag-bio giants (e.g. Monsanto, Syngenta, etc.). Examples of such companies include **Abundant Robotics, DJI Innovations, Climate Corporation,** and **Blue River Technology**.

Start-ups such as **Orbital Insights**, **Gro Intelligence**, **Descartes Labs**, and **Tellus Labs** are developing yield prediction algorithms based on a combination of satellite imagery analysis, weather data, and historical yield data. Tellus Labs claims to be more accurate than USDA reports with predictions being available one month prior to the first USDA report in July.

Planting, maintaining, and harvesting crops requires time, energy, labour and resources. In-field monitoring relies on a combination of drones and in-field cameras with elevated computer vision capabilities to monitor crops and field conditions in real time. For example, **Resson**, a Monsanto Growth Ventures company, has developed image recognition algorithms that can identify plant pests and diseases more accurately than humans. Resson has a partnership with **McCain Foods**, to help McCain minimise losses in their potato production supply chain. As far as software is concerned there are companies like **Prospera** which employ deep learning-based computer vision to monitor crops in real time.

Companies active in the field of crop and soil health analysis use a range of AI technologies to monitor and determine the effects of microbes and other pathogens on plant health. In addition, they investigate mutations, genetic and metabolic pathways that may have a harmful effect on the plant or that might be able to increase yields.

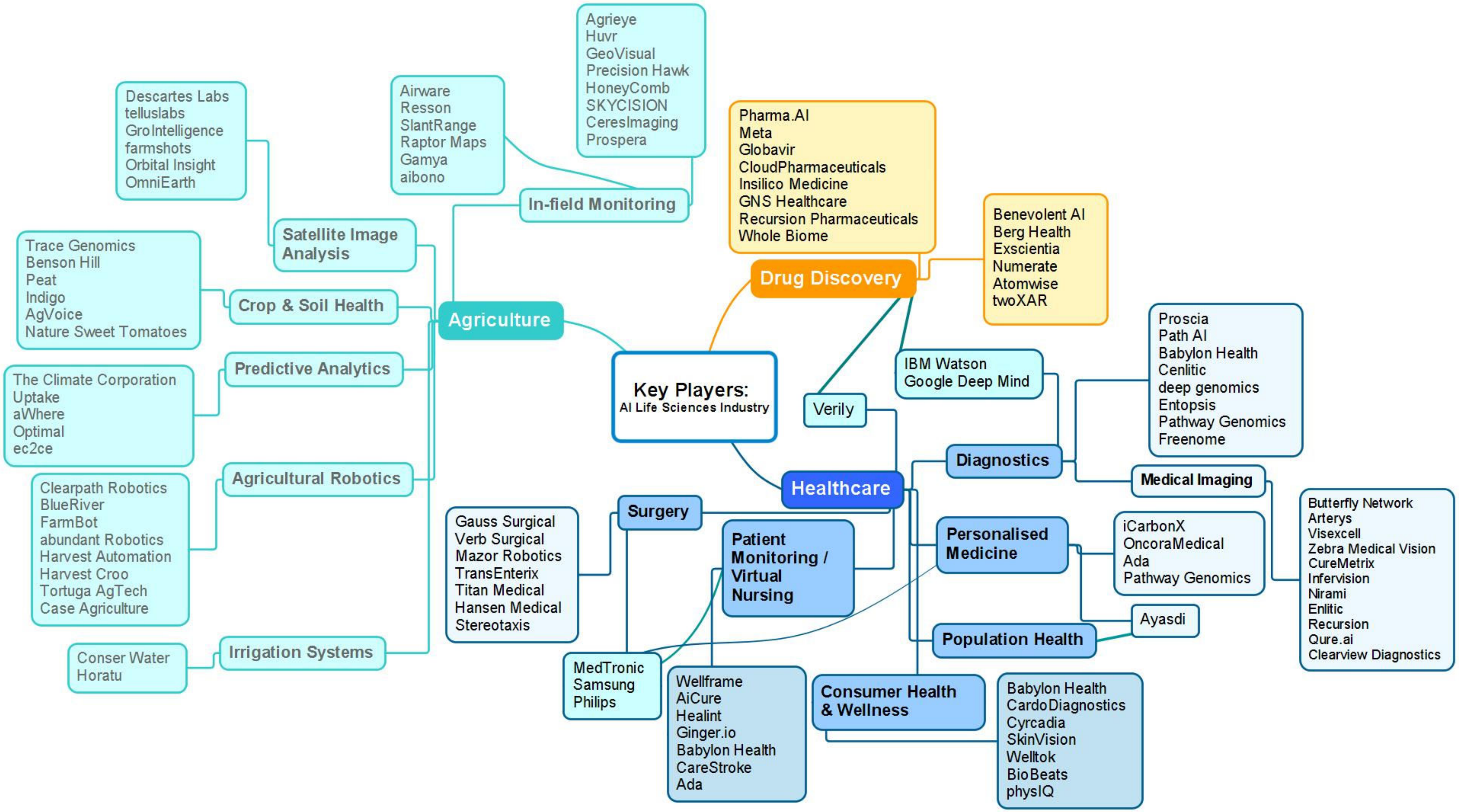
Indigo Agriculture is a firm that uses AI technology to analyse and harness the plant microbiome, while **Benson Hill Biosystems**, which has raised over $34 million in funding, uses CropOS, a cognitive engine that integrates crop data and analytics with biological expertise to identify the most promising plant genetics. The proprietary CropOS platform utilizes data from DNA and RNA sequencing, field trials, and imaging analytics to identify gene expression patterns and relate them to a specific phenotype. With each new data set, the CropOS platform re-calibrates and learns, improving its predictive capability.

NatureSweet is experimenting with AI technology to monitor tomato health throughout the growing season. NatureSweet's platform relies on a combination of cameras that take frequent images of the plants in the glasshouse, and an algorithm that identifies visual cues of emerging issues like pests and disease. The instantaneous feedback to the farmers allows them to significantly reduce the response time and application of the necessary countermeasures. According to NatureSweet, application of their AI system results in yield increases of 2-4%, with that number expected to climb in excess of 10% as the system gets further optimised.

Agricultural robotics include a range of robots that can perform a wide variety of agricultural tasks. For example**, Abundant Robotics**, a **Stanford Research Institute** spin-out, has developed robotic systems for fruit harvesting. Abundant Robotics employs the latest form of computer vision to recognise ripe apples and a vacuum system to collect them. In May 2017, it announced funding of $10 million to commercialise its apple-picking robot.

Perhaps the best example of successful implementation of AI in agriculture is **Blue River Technology** (**BRT**), another **Monsanto Growth Ventures** company. BRT develops robots that use computer vision and machine learning for agricultural applications. BRT's "see and spray" technology enables farmers to spray herbicides towards eliminating weeds in cotton fields only where weeds are present. This highly precise and targeted spray application can detect the presence and location of weed species and reduce herbicide usage up to 90%. According to BRT's website, the company is also developing a "LettuceBot" to thin lettuce populations and a drone imaging system that collects data from fields.

The key players are mapped according to sector and main technology areas in the Figure below. Note this is not an exhaustive list but rather a collection of important companies identified during this research.



Key Players:
AI Life Sciences Industry
Agriculture
Satellite Image Analysis
Descartes Labs
telluslabs
Gro Intelligence
farmshots
Orbital Insight
OmniEarth
In-field Monitoring
Airware
Resson
SlantRange
Raptor Maps
Gamya
aibono
Agrieye
Huvr
GeoVisual
Precision Hawk
HoneyComb
SKYCISION
CeresImaging
Prospera
Crop & Soil Health
Trace Genomics
Benson Hill
Peat
Indigo
AgVoice
Nature Sweet Tomatoes
Predictive Analytics
The Climate Corporation
Uptake
aWhere
Optimal
ec2ce
Agricultural Robotics
Clearpath Robotics
BlueRiver
FarmBot
abundant Robotics
Harvest Automation
Harvest Croo
Tortuga AgTech
Case Agriculture
Irrigation Systems
Conser Water
Horatu
Drug Discovery
Pharma.AI
Meta
Globavir
CloudPharmaceuticals
Insilico Medicine
GNS Healthcare
Recursion Pharmaceuticals
Whole Biome
Benevolent AI
Berg Health
Exscientia
Numerate
Atomwise
twoXAR
IBM Watson
Google Deep Mind
Verily
Healthcare
Diagnostics
Proscia
Path AI
Babylon Health
Cenlitic
deep genomics
Entopsis
Pathway Genomics
Freenome
Medical Imaging
Butterfly Network
Arterys
Visexcell
Zebra Medical Vision
CureMetrix
Infervision
Nirami
Enlitic
Recursion
Qure.ai
Clearview Diagnostics
Personalised Medicine
iCarbonX
OncoraMedical
Ada
Pathway Genomics
Ayasdi
Population Health
Surgery
Gauss Surgical
Verb Surgical
Mazor Robotics
TransEnterix
Titan Medical
Hansen Medical
Stereotaxis
Patient Monitoring / Virtual Nursing
MedTronic
Samsung
Philips
Wellframe
AiCure
Healint
Ginger.io
Babylon Health
CareStroke
Ada
Consumer Health & Wellness
Babylon Health
CardoDiagnostics
Cyrcadia
SkinVision
Welltok
BioBeats
physIQ

For this white paper, we have provided more information on several prominent companies in more detail below, along with summary tables of additional companies. The table at the end of each section and in Appendix 1 describes additional companies and deals in the space.

These companies' activities have been described and, where possible, compared using the following parameters, which provide an indication of their strengths and longer-term strategies:

- Number of disease areas they cover
- Number of industry sectors they operate in
- Number of partnerships/collaborations
- Number of acquisitions or spin-outs
- Funding raised from venture financing

The scores based on the number of partnership deals, sub-sectors, acquisitions or spinouts and disease areas where applicable, range from 0 to 10 for each of the factors. Any score greater than 10 is noted only as 11. This information is displayed on radar charts for each company in the sections below.

To allow venture financing to be represented on each chart, this has been scored by the band of funding raised, as outlined in the Table below.

Score	Total Investment ($ million)
1	0 – 15
2	15 – 30
3	30 – 45
4	45 – 60
5	60 – 75
6	75 – 90
7	90 – 105
8	105 – 120
9	120 – 135
10	135 – 150
11	>150m

HEALTHCARE

Companies currently dominating the $1,731 billion global healthcare market include the big pharma companies like **Novartis**, **Pfizer**, **GSK**, **J&J**, **Abbott**, **Novo Nordisk** as well as the medical device and supporting companies such as **Medtronic**, **Philips**, **GE Healthcare**, **Fujitsu, Cermer Corp, Siemens** and **McKesson**. The introduction of sophisticated digital and AI technology over the past few years has resulted in a number of new entrants to healthcare – largely from the digital and computer software industry. These recent entrants include: **Google, Intel, IBM Watson, Proscia, Philips, PathAI, ContextVision, OptraSCAN, Discovery Health** and **Sig Tuple**.[11] According to the same research, academic institutions and non-healthcare companies have so far been earlier and faster in their adoption of AI in healthcare.

In terms of AI technology breakdown some of the key companies competing in each sector within healthcare are described below. Notably, the majority of these companies are not traditional healthcare or pharma companies but are gaining influence in the sector (adapted from Frost & Sullivan). In addition, a number of academic institutions are leading in terms of technology development.[27]

Technology	Example Companies
Deep Learning	Atherys, Butterfly Network, Lunit, Qure.ai, Samsung
Robotics	ARTAS, Google, J&J, RT Works, Cyberdyne, Panasonic
Digital Personal Assistant	Amazon, OpinionX, BOND.AI, Siri
Natural Language Processing	Nuance, IBM, Apache, Intermountain, QPID Health
Machine Learning	Amazon, Google, Human Dx
Image Processing	La Trobe University
Speech Recognition	Mozilla, CNRS-Thales , Nara Institute of Science & Technology, Pusan National University Hospital
Big Data Analytics	Innoplexus, Biovista, Solix Technologies
Predictive Modelling	Google, Quant HC, Biogen, Roundtable Analytics, BioTherapeutics, eQHealth Solutions

MEDTRONIC & MAZOR ROBOTICS

Sector: robot-assisted surgery

Medtronic, a global medical device manufacturer, is a key player in the robot-assisted surgery market, after **Intuitive Surgical** which is currently the market leader with its Da Vinci surgical machines. Medtronic are investing heavily in AI assisted surgery, largely through a partnership with **Mazor Robotics**, an Israeli surgical robotics company. The company has invested $72 million in Mazor and has a 10.6% share of equity as of August 2017.[51]

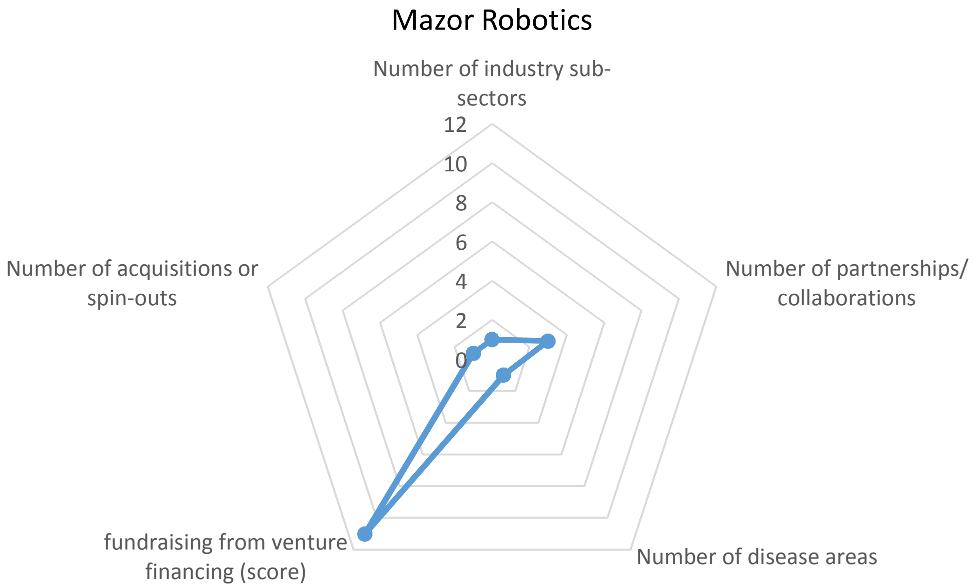
- The company first invested $20 million for 3.4% equity in early 2016.
- The company acquired 15 Mazor systems during 2016.
- Invested a further $12 million in July 2016.
- Medtronic is Mazor Robotics' sole partner for developing and commercialising robot-assisted spine surgery devices.
- The deal terms set annual minimum Mazor X purchases over a 4.5 year period.

[51] https://orthofeed.com/2017/08/30/medtronic-puts-another-40m-into-mazor-robotics/

Medtronic has 150 employees working on its robotic systems business across the US and Europe. They are aiming to lower the costs associated with robotic surgery.

Mazor have a CE-approved surgical system called Mazor X Align – the Mazor X range has a number of products under development called Mazor X Lateral and Mazor X SIJ. They have another device called ArcAid, all of which are targeting orthopaedic surgery.

The company received its first seed round funding in 2004 from a consortium of investors including **Johnson & Johnson Innovation**. They have since raised approx. $180 million in a number of venture funding rounds from J&J and Medtronic as well as investors such as **Oracle Investment Management**. Alongside its development partnership with Medtronic, the company has a licensing agreement with the **Cleveland Clinic**, and an acquisition deal with **Baptist Medical Centre Jacksonville**.



VERILY & VERB SURGICAL

Sectors: robot-assisted surgery; imaging & diagnostics; personalised medicine; patient monitoring

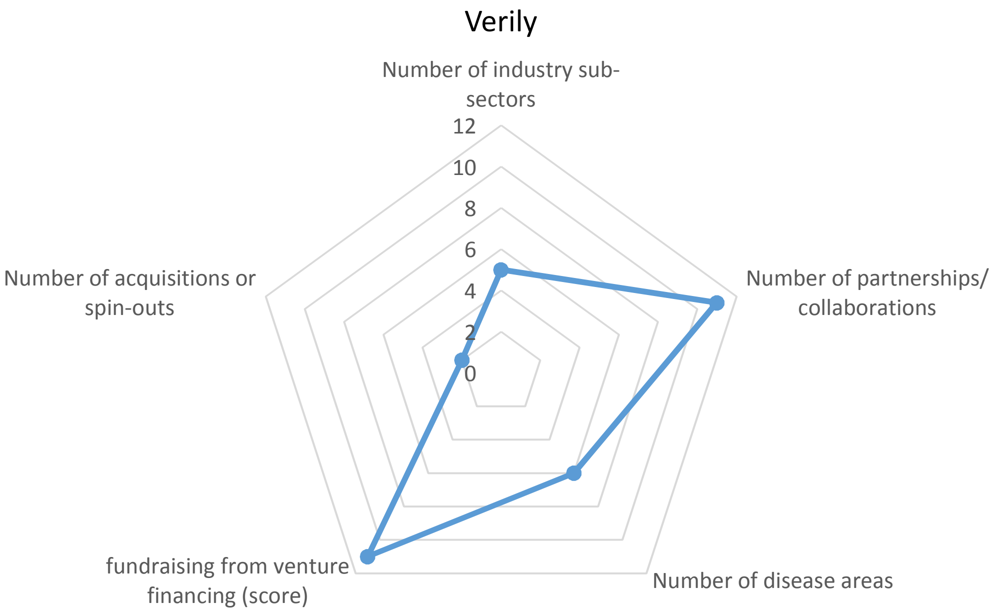
Verily, formerly the **Google** Life Sciences division, now **Alphabet Inc**., is working at the intersection of technology, data science and healthcare. The company has a number of projects and joint ventures developing tools to collect and organise health data, create interventions and platforms that put insights derived from that health data to use for more holistic care management.

The company are working with a broad set of companies and academic institutions: **Alcon, Biogen, Dexcom, Ethicon, GSK, Galvani, Nikon, Sanofi, Verb Surgical, 3M, Bringham and Womens Hospital, NHS Hospitals, Duke University School of Medicine, Parkinson Net, Radbound University** and **Stanford Medicine**. In addition the company invested in **Freenome**, an early-stage cancer detection company.

Example partnerships:

- **Verb surgical** – **Johnson & Johnson**, through its medical device company **Ethicon**, and Verily, established a joint venture for surgical intervention incorporating robotics, visualisation, advanced instrumentation, machine learning and connectivity.
- MS Observational study – carried out in partnership with **Biogen and Bringham Women's Hospital** to decipher why multiple sclerosis (MS) progresses so differently among diagnosed individuals and glean insights for improved care initiatives. The project harnesses biological, behaviorual and enviornmental data using software, machine learning and other computational techniques to gather insights.
- NHS Early invervention program. The company is partnering with **NHS Heywood, Middleton and Rochdale Clinical Commissioning Group** and **Merck Sharp & Dohme** (MSD), on a NHS England test bed project aimed at identifying patients who are at risk of chronic conditions. They are harnessing analytical tools to develop insights from patient data.
- Smart Lens program in partnership with **Alcon** for monitoring glucose in contact lenses and to accomotate vision correction in far sightedness.
- Miniaturised continuous glucose monitors for diabetes. Partnering with **Dexcom** to develop an adhesive patch with monitoring and data sharing capability.

The company are working across healthcare sub-sectors such as imaging & diagnostics, personalised medicine, robotic-assisted surgery, patient monitoring. Some of the disease areas they are working on include diabetes, eye-related diseases, retinal imaging, parkinsons, multiple sclerosis and metabolic disease.



The joint venture between Verily and Ethicon (Verb Surgical), founded in 2015, is focused on robot-assisted surgery; developing an intelligent digital surgery platform that will incorporate robotics, visualisation, advanced instrumentation, machine learning and connectivity into a total solution for operating room professionals. The corporate owners are thought to have invested approximately $250 million in the venture.

Verb Surgical's approach involves harnessing AI for image-guided MRI and CT scans during surgery. The surgical technology was developed by Ethicon and research centre, **SRI International**. Verily are providing data analytics, machine learning and connectivity capabilities as well as advanced software and operating systems. They are harnessing machine learning algorithms like Google Brain, TensorFlow and DeepMind. In addition the company expect the surgical instrument capabilities such as teleproctoring, monitoring, and training to be enhanced with other Google technologies, like Google Hangouts, Google Translate, and in-development augmented reality and virtual reality technologies.

There are more than 200 people working on the digital surgery platform, including around 100 people at Verb Surgical, 50 people from Johnson & Johnson, and 50 from Verily. The company has corporate and clinician partnerships, with the aim of democratising surgery. Limited information is available on these collaborations.

PHILIPS

Sectors: population health management; personalised medicine; patient monitoring; imaging & diagnostics; virtual nursing

Philips are developing and launching a number of AI-based connected health solutions to deliver actionable insights to improve outcomes, increase access to quality care and reduce costs. They are positioned well with market leadership in electronics as well as consumer health and the medical sector expertise.[52]

The company is focused on population health management, acute healthcare informatics and personal health solutions which integrate to the cloud. They are an example of a company growing AI capabilities from their informatics and data analytics capabilities. They are using adaptive intelligence, which is an emerging concept of combining domain specific models and knowledge (e.g. in the field of radiology), and AI to create an adaptive and contextual experience, anticipating users and augmenting their work. The release of Philips Illumeo is their first product harnessing adaptive intelligence. It is an imaging and informatics AI technology designed to help interpret and share medical images, and is currently designed for radiology analysis. The intelligent software is the first to combine contextual awareness capabilities with advanced data analytics to assist radiologist workflow.

Philips IntelliSite Pathology Solution is another automated digital pathology system that includes a slide scanner, image management system and software tools. Philips acquired **PathXL** in 2016 and has recently announced a partnership with **PathAI**, a diagnostics start-up company (summarised below), to improve AI breast cancer diagnostics.

[52] https://aibusiness.com/how-is-philips-improving-healthcare-through-ai/

Philips's work using AI is tightly interwoven with their capabilities in healthcare software, personalised medicine (genomics) and population health management. For example:

- Debut of IntelliSpace Enterprise Edition, industry-first managed service solution for hospital-wide clinical informatics and data management
- Philips HealthSuite is a secure ecosystem of integrated health IT, software, solutions and services which offers patients, clinicians, and healthcare executives advanced tools at the point of care. Focused on personalised health from prevention to diagnosis, treatment and home care.
- Jovia Coach, a smartphone app that combines technology with human coaching for people at risk of type 2 diabetes, the company have an advanced telehealth system, eICU soloutions for critical care and hospital bed management. They also have a suite of continuous care home monitoring solutions.

Deals and partnerships in the area include:

- The acquisition of **Wellcentive**, with expertise in aggregating and analysing patient data to improve health outcomes inside. Now **Phillips Wellcentive**, the company will analyse 1.5 billion data points of hospital data on a continuous basis.
- Philips announced a partnership with **Nuance**, a leading provider of intelligent voice and language solutions that provides 70% of radiology reports in the US.[53]

BABYLON HEALTH

Sector: virtual nursing

A UK-based digital health services company has developed a solution for disease diagnostics with an AI doctor chabot technology delivered to the patient via a smartphone app. The company raised approximately $60 million in April 2017. Trials of the technology are currently ongoing in London, where the Babylon technology is being tested as an alternative to the non-emergency NHS 111 number using the GP-at-hand app. The app allows users to seek immediate healthcare advice on symptoms, triaging and appointment booking. The app will ask follow-up questions based on the information the patient provides, in order to determine the illness and seriousness of the condition. The app will then advise on next steps: medical assistance, appointment, pharmacy or self-management at home.

The company has venture backing from investors including **Kinnevik** and **Google DeepMind**.

[53] https://www.nuance.com/about-us/newsroom/press-releases/philips-and-nuance-bring-ai-into-radiology-reporting.html

ADDITIONAL COMPANIES: HEALTHCARE

Company	Sector	Description
Qure.ai	Imaging & Diagnostics	The India and California-based company has developed deep learning algorithms to detect and highlight abnormalities in medical images to reduce the chances of a misdiagnosis. Focus on MRI scans, X-rays to identify tumours in brain, lung and abdomen. The company is working in the field of radiology.
Butterfly Network	Imaging & Diagnostics	The company are focused on imaging, and have developed solutions for whole body imaging using deep learning AI technologies. The company has created a portable medical imaging device integrated with a deep learning assistant that helps to diagnose patients in remote areas where clinicians aren't available or are less likely to specialise.
Enlitic	Imaging & Diagnostics	The company is using deep learning in diagnostics. It has a partnership with Capitol Health Limited, an Australia-based diagnostic imaging services company to utilise deep learning diagnostics in analysis of medical CT images for lung cancer and bone fracture detection.
AiCure	Patient monitoring	The company is using AI solutions for patient stratification for clinical trials and patient behaviour to target poor drug adherence, targeting the efficiency losses from lack of treatment compliance. The platform is a visual recognition platform using computer vision and deep learning technology to confirm the patients taking part in clinical trial are taking their medications. The company estimates that 20-30% of drugs fail because patients aren't following protocol. The company are backed by investors including New Leaf Venture Partners and Pritzker Group Venture Capital.
CareStroke	Patient monitoring	Leverages Google's TensorFlow and Hadoop to identify at risk patients by combining clinical, behavioural, demographic and socioeconomic information.
Ada	Personalised health, Virtual Nursing	The London and Berlin based health technology start-up is a personal health companion and telemedicine or virtual nursing app. The company is working on an AI powered doctor, empowering people to make decisions about their health. Ada has been trained using real world cases and is powered by AI combined with an extensive medical knowledge base covering many thousands of conditions, symptoms and findings. In each assessment, Ada takes all patient information into consideration, including past medical history, symptoms, and risk factors. Through machine learning and multiple closed feedback loops, Ada continues to grow more intelligent. Its key competitor is Babylon.

Company	Sector	Description
SkinVision	Consumer Health & Wellness	The skin cancer app uses computer vision to analyse skin lesions, it has received funding from dermatology company LEO Pharma
Nirami	Imaging & Diagnostics	Indian company is focused on breast cancer screening using a multi-patented solution, SMILE, which harnesses high resolution thermal images and AI to provide reliable, early and accurate breast cancer screening. Early results, from data of 300 patients collected in two hospitals and one diagnostic centre, demonstrate high accuracy, which remains to be validated in large-scale pilot studies.
Proscia	Imaging & Diagnostics	Image guided pathology testing. The company have developed a pathology cloud platform that uses computer vision to analyse biopsy slides and medical images with a primary focus on oncology.
Infervision	Imaging & Diagnostics	The Beijing based company uses algorithms and computer vision methods to support lung cancer diagnosis. It is a second pair of eyes for the radiologist and can identify >20 different cardiothoracic lesions.
OncoraMedical	Personalised Medicine	The start-up is harnessing AI to bring predictive insights and risk analytics to radiation oncology.
Zebra Medical Imaging	Imaging & Diagnostics	Zebra is focused on radiology imaging solutions. The platform is harnessing AI to diagnose medical conditions and trends to identify high risk patients, facilitate disease prevention and optimise workflow.
iCarbonX	Personalised Medicine	The China based healthcare AI company developing a platform to facilitate precision medicine, nutrition, preventative care and disease treatment. The core focus of the company is on solutions for personalised medicine. The start-up raised a series A of $154m in 2016.
PathAI	Imaging & Diagnostics	The company is using machine learning and deep learning techniques in the pathology arena to drive faster, more accurate diagnosis of diseases. The company has partnerships with Philips in the area of clinical precision; drug development with Bristol-Myers Squibb and global health with the Bill & Melinda Gates Foundation.
Clearview Diagnostics	Imaging & Diagnostics	An AI software company developing tools to assist clinicians in disease diagnostics with a primary focus on breast cancer, they are also examining additional applications. The company is working towards FDA approval, the tool could drive down radiologist workloads freeing up time to focus on their patients whilst dealing with more difficult cases.
CureMetrix	Imaging & Diagnostics	The California based start-up has developed an algorithm for image analysis, which is currently being tested to identify lung cancer in x-rays and for breast cancer detection in mammograms.
Freenome	Imaging & Diagnostics	A genetics start-up based in Philadelphia, USA is focused on machine learning for analysing blood samples to categorise cancer stages

Company	Sector	Description
Entopsis	Imaging & Diagnostics	The start-up based in Miami is building a device called Nutec (Nanoscale Unbiased Textured Capture) in oncology as well as autoimmune diseases and rare diseases.
Gauss Surgical	Surgery	The company is developing real time blood monitoring solutions for accurate and objective estimation of blood loss, helping to optimise transfusion and safer surgery.
Verb Surgical	Surgery	Working to develop next gen surgical robots combining advanced visualisation, machine learning, data analytics and connectivity. The company are working with Ethicon (Johnson & Johnson company) and Alphabet Inc’s Verily.
TransEnterix	Surgery	A medical device company which is pioneering the use of robotics to improve minimally invasive surgery. They have developed ALF-X a multiport robotic surgery system with up to 4 arms to control instruments and a camera; similarly SurgaBot is a single incision robotic assisted surgery system.
Hansen Medical	Surgery	The company develops and manufactures medical robotics designed for the positioning, manipulation and control of catheters. In 2016 the FDA approved Hansen's Megellan Robotic Catheter.
Stereotaxis	Surgery	The company designs robotic systems for treatment of abnormal heart rythms. Niobe ES robotic system and Vdrive system. The company has strategic alliances with Siemens and Philips Medical Systems.
Flatiron Health	Hospital workflow	Flatiron Health is a healthcare technology company and operator of the OncologyCloud platform. Integrating across multiple clinical data spectrum, Flatiron Health is targeting cancer care providers and life science companies to gain deep business and clinical intelligence through its portfolio of web-based platforms. These include: OncoEMR (workflow efficiency), OncoBilling, OncoAnalytics, OncoTrials, and value-based oncology tools.
Cyrcadia Health	Consumer Health & Wellness	The Nevada-based start-up has developed a breast patch to detect temperature changes in breast tissue, and the data is analysed using machine learning algorithms. It raised a $2.15M Series A round in 2014, and an undisclosed round in 2016
Pathway Genomics	Personalised Medicine; Imaging & Diagnostics	The company has developed a blood test kit, Cancer Intercept Detect, and is collecting blood samples from high-risk individuals who have never been diagnosed with cancer, as part of a research study to determine if early detection is possible. The company received a $40M Series E funding from the IBM Watson Group in Q1’16.

DRUG DISCOVERY

There are a number of key companies developing AI platforms for application in drug discovery. Most of these are start-up companies, however two leading the space include **IBM Watson** and **Google DeepMind Health**. In addition, a number of pharmaceutical companies are embarking on deals across the sector.

IBM

Sectors: drug discovery, diagnostics, medical imaging, personalised medicine, population health management

IBM Watson, part of **IBM**'s cognitive solutions business, is the most well-known machine learning model for drug discovery and a pioneer in the field. IBM is estimated to have approximately 45% of the market for AI-related healthcare and drug discovery.[8] In the first half of 2017, cognitive solutions generated $8.6 billion in revenue – nearly one-quarter of IBM's total revenue. The company is one of the leading acquirers of healthcare computing companies, having spent approximately $4 billion in the two years to June 2017 on such deals to expand its AI capabilities.[49]

A key function of IBM Watson is to identify drug candidates by synthesising large amounts of textual and laboratory data to quickly analyse the set and identify new hypotheses. The data include laboratory data, clinical reports and scientific publications. The key benefit is to save researchers time, increasing research efficiency to make evidence-based decisions. The tool has extended beyond drug discovery to healthcare and medical diagnosis.

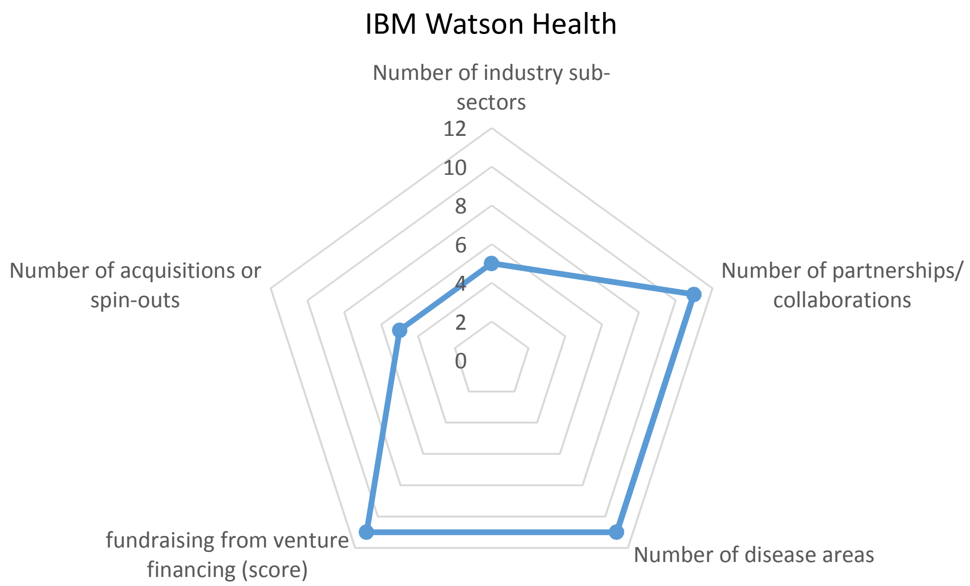
The company's activities cover optimising performance and identifying solutions in life sciences, oncology, value-based care, government and imaging. Watson for Oncology, which gives treatment recommendations based on patients' medical records announced in 2016 that 21 hospitals across China will start using the cognitive computing platform, previously deployed in India and Thailand.

Watson also launched a project called WatsonPaths in collaboration with the **Cleveland Clinic Lerner College of Medicine** of **Case Western Reserve University** in the US. WatsonPaths consists of two cognitive computing technologies that can be used by the AI algorithm, Watson, which are expected to help physicians make more informed and accurate decisions faster and to cull new insights from electronic medical records (EMR).

IBM Watson maintains its dominance and has made a number of significant deals and partnerships in the sector. It has acquired several companies in the past two years: **Ann Arbor**, **Truven Health Analytics** ($2.6 billion); **Merge Healthcare**, a medical imaging company ($1 billion); **Phytel**, a population health company; and **Explorys**, a healthcare intelligence company.[35] Furthermore they have established a partnership with **Pfizer** to support the company's immunoncology pipeline, and additional partnerships with **Novartis, Novo Nordisk, Celgene, CVS Pharmacy** and the **FDA.**[46] In the arena of medical diagnosis the company is partnering with **Memorial Sloan Kettering Cancer Centre** and the American private healthcare company, **Wellpont**.[54]

[54] http://www.wired.co.uk/article/ibm-watson-medical-doctor

The company does not specify revenues attributable to Watson Health, but they state that their software is being used by approx. 12 of the largest life science companies, and its oncology tools by more than 55 hospitals and healthcare organisations worldwide.



GOOGLE DEEPMIND HEALTH

Sectors: imaging & diagnostics; personalised medicine

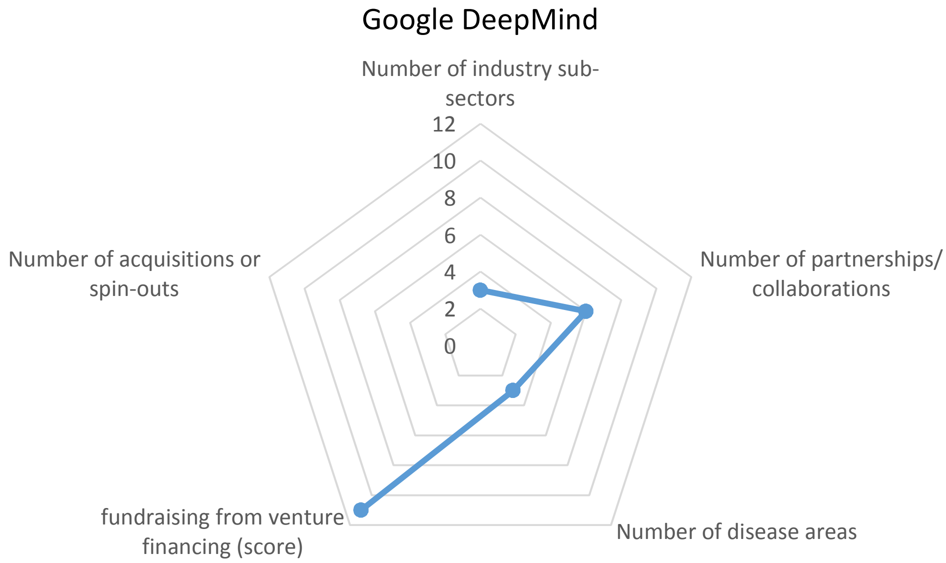
Google acquired **DeepMind** in 2014 (established AlphaGo software) for approximately £400 million. DeepMind had raised $50 million prior to the Google acquisition. The company established **Google DeepMind Health** which subsequently began working with NHS hospitals in the UK (2016) with the aim of developing solutions for identifying early signs of disease ultimately resulting in blindness or cancer. The company is leveraging machine learning to analyse eye scans which are typically difficult to analyse. It is also focused on developing new clinical mobile, alerts, messaging and task management apps linked to electronic patient records. It has developed a clinical alert app called Streams, for acute kidney injury (AKI).

Partnerships which have been announced with several NHS Trusts include**: Imperial College Healthcare NHS Trust, Royal Free Hospital London, University College London Hospital** and **Moorfields Eye Hospital**, Taunton, and **Somerset NHS Foundation Trust**. The UCL partnership began in 2016 with the radiotherapy department – DeepMind will test the use of the machine learning tool to help reduce the time it takes to plan radiotherapy treatment for hard-to-treat cancers of the head and neck. The partnership and exchange of patient data has been the subject of some controversy in the UK between 2016 and 2017, with a review underway by the Information Commissioners Office, the data protection watchdog.[55] In parallel the company is working with academics at the **Cancer Research UK** centre at

[55] http://www.independent.co.uk/life-style/gadgets-and-tech/news/google-deepmind-nhs-patients-data-deal-1-million-legal-inappropriate-dame-fiona-caldicott-a7738601.html

Imperial College London with a view to improving breast cancer detection using mammogram images.

The company hired two academic teams of founders (seven people in total) behind **Dark Blue Labs** and **Vision Factory**, two UK-based deep learning start-ups. It is also partnering with academics **at Oxford University**. DeepMind has also invested £17.4 million in **Babylon Health**, the digital health company partnering with the NHS to develop patient triaging and virtual nursing app solutions.



BENEVOLENT AI

Sectors: Drug Discovery

In a similar approach to **IBM**, **Benevolent AI**, based in London, has developed machine learning capabilities and algorithms to mine research literature, molecular data and proprietary research databases. The company is focused on repurposing or resurrecting existing assets in which significant investment has already been made. The tool improves the selection of candidates and drug targets using their AI analytical capability. The company has raised more than $140.6 million in funding since 2013 and has a valuation of approx. $1 billion (2017). Their pipeline includes more than 20 programmes in preclinical development.[56]

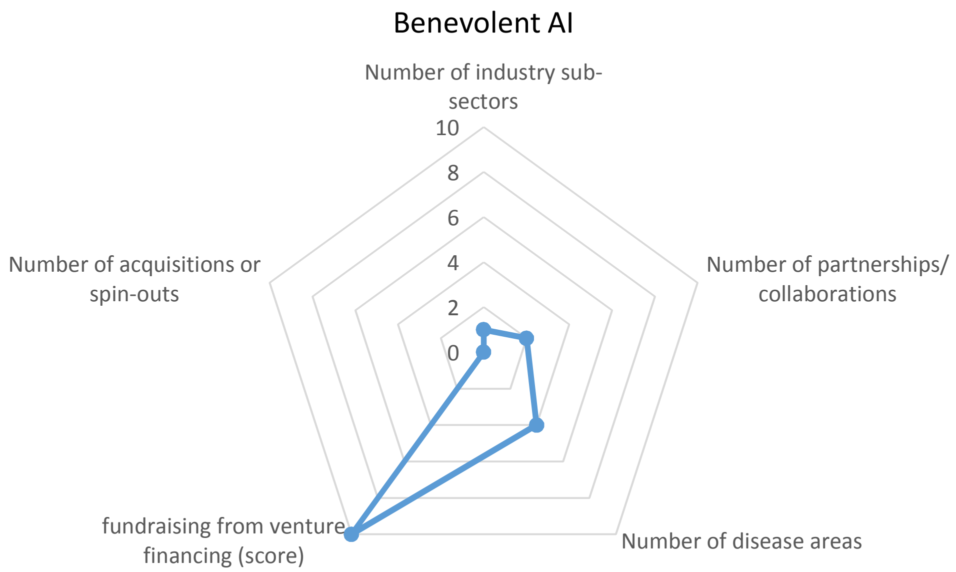
The AI platform analyses molecular data, study findings (both positive and negative), and unstructured data related to compound efficacy, but combines it with a host of commercially relevant reimbursement and outcomes data that can inform strategic decision-making. Initial testing resulted in generation of 36 new hypotheses and 24 validated targets *in vitro*. By traditional biopharma R&D timelines, only 5 candidates could have been managed in the same timeframe.

[56] *Insights in Healthcare Horizons*, CB Insights (2017)

The platform, a Judgement Augmented Cognition System, applies natural language processing, deep learning and other algorithms to build a knowledge graph, showing the complex pattern of interactions between various molecular entities and diseases. This allows the company to generate new potential associations or rule out existing hypotheses.

The company has entered into a number of agreements, in-licensing promising compounds for development in house. Notably, a deal with **Janssen** has so far resulted in progression of a candidate to phase II clinical trial. The model Benevolent has adopted, unlike many AI companies, is not a service or platform drug discovery provider. The strategy is to build its own pipeline, as such it has licensed a number of small molecule candidates along with clinical and biological data to seek novel indications for them. The first candidate is expected to move into phase IIb trials at the end of 2017. The disease areas of focus include inflammation, neurodegeneration (Parkinson's; Alzheimer's) and orphan diseases such as Amyotrophic Lateral Sclerosis (ALS) and rare cancers.

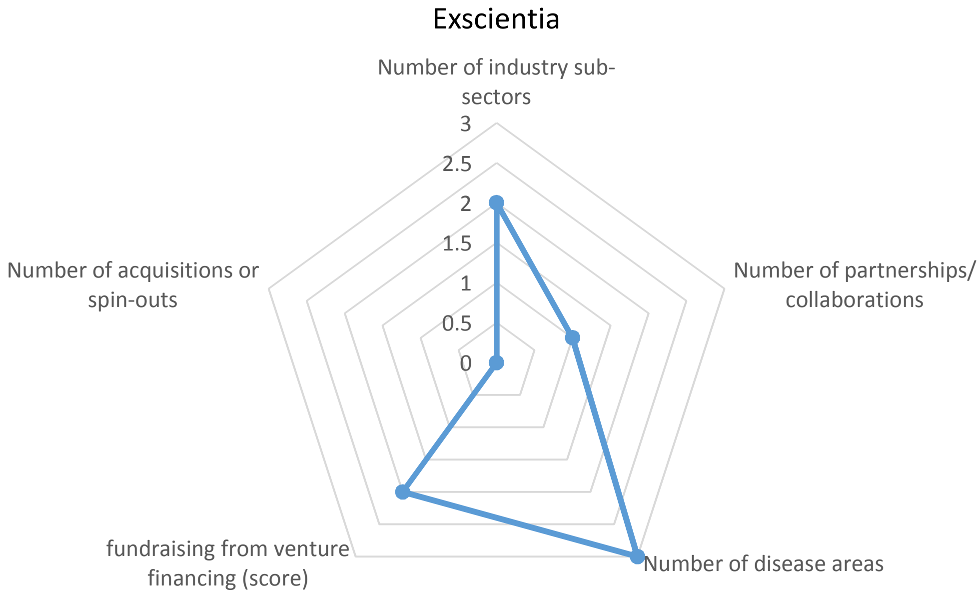
In the Janssen deal, Benevolent will pay royalties and certain milestone payments if the company moves the candidate into Phase III. Benevolent also has a drug discovery collaboration with **MRC Technology** to conduct complex chemistry studies on disease targets selected by Benevolent.



EXSCIENTIA

Sectors: drug discovery

An AI-based drug development company based in Scotland, spun out of the **University of Dundee**, **Exscientia** is utilising AI to automate the drug discovery process by harnessing existing experimental data and published information. The company received $17 million investment from **Evotec** in September 2017. It follows a collaboration between the two companies which began in early 2016, focused on immunocology candidates.[57] The company announced a strategic research collaboration with **Sanofi** in May 2017, with a license option agreement focused on metabolic disease. In particular for disease indications such as diabetes.[58]



ATOMWISE

Sectors: drug discovery

Atomwise is a San Francisco-based drug discovery AI company with a deep learning platform for small molecule discovery, AtomNet. The company have launched 27 drug discovery projects in partnership with pharma companies such as **Merck** and **Abbvie**. The company also has a programme with university laboratories where up to 100 laboratories will receive 72 potential medicines generated by AtomNet for further development. In addition the company has reported identification of two compounds which have strong potential in treatment of Ebola viral infection.

The company has secured approximately $6 million in funding from investors such as **Khosla Ventures, Data Collective, Draper Fischer Jurvetson, AME cloud ventures** and **Y Combinator**.

[57] http://www.globaluniversityventuring.com/article.php/6119/evotec-designs-17.7m-exscientia-deal

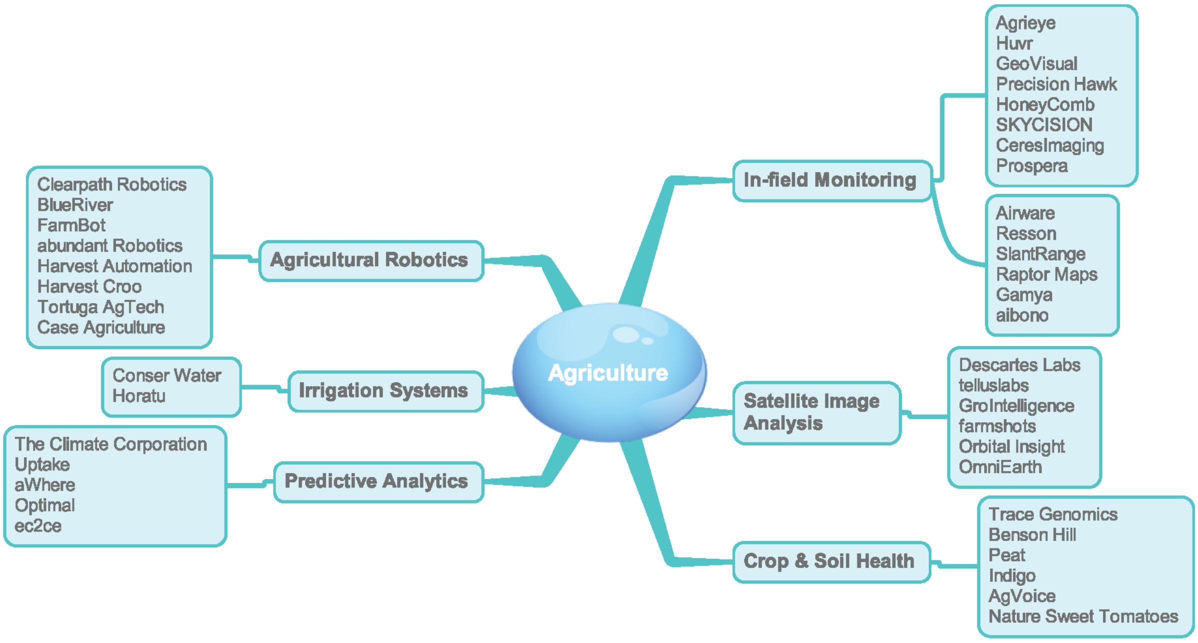
[58] https://www.exscientia.co.uk/news/2017/5/9/sanofi

ADDITIONAL COMPANIES: DRUG DISCOVERY

Company	Sector	Description
Berg Health	Drug Discovery	The company are developing an AI drug discovery platform with a mission to upturn the entire pharmaceutical R&D process. The company initiated a phase II clinical trial in 2016 for a drug compound that could potentially treat pancreatic cancer and has funding support from Silicon Valley investor Carl Berg. The company announced a partnership with Sanofi in September 2017 to focus on infectious disease and smart vaccine development, in particular to target influenza across populations where the vaccine is ineffective.
Meta	Drug Discovery	A Canadian AI company developing a solution to unpick disease progression. The company was bought by the Chan Zuckerberg Initiative in January 2017. The charity has a mission to eradicate disease.
Numerate	Drug Discovery	Numerate, founded in California USA, was established to analyse chemical design in drug discovery. The technology basis takes advantage of the large volumes of data from drug discovery, applying it to chemical design. In a deal with Takeda Pharma, the company will provide drug candidates by virtual compound screening against targets. The tool will step further to design and optimise compounds, modelling the pharmacokinetic process from absorption to distribution, metabolism, excretion and toxicity.
TwoXAR	Drug Discovery	The US-based company is an AI biopharmaceutical company employing a computational platform to screen data on thousands of drug candidates to identify associations between drugs and disease progression which have not yet been elucidated. The company has published information on positive pre-clinical data for candidates in therapeutic indications of rheumatoid arthritis, liver cancer and type 2 diabetes. The company has university and hospital partnership with Stanford Medicine, Mount Sinai and Santen Pharmaceutical. They have so far raised $3.4 million in funding from investors such as CLI Ventures and StartX.
Pharma.AI	Drug Discovery	The artificial intelligence division of Insilico Medicine, a bioinformatics company associated with John Hopkins University in the US launched in 2016. The company focuses on drug discovery platforms for cancer, Parkinson's disease, Alzheimer's and other ageing and age-related health issues.
Globavir	Drug Discovery	The immune-oncology start-up uses a machine learning platform to reduce drug discovery times. The company has a partnership with Sorrento Therapeutics under which it has licensed its lead oncology compound.
Recursion Pharmaceuticals	Drug Discovery	Combines biological sciences with machine learning techniques to identify new disease treatments.
InSilico Medicine	Drug Discovery	The Maryland-based start-up applies deep learning algorithms to drug discovery for applications including cancer immunotherapy. It received an undisclosed seed amount from Hong Kong-based Deep Knowledge Ventures in 2014
Whole Biome	Drug Discovery	The company are using an AI based platform, genomic and analytical tools to develop microbiome based insights. They are partnering with the Mayo Clinic to develop diagnostic solutions against preterm labour.

AGRICULTURE

While AI is still in its infancy, many tech companies are gearing up for dramatic growth in the implementation of AI in agriculture. The key players are summarised in the following mind map.



The leading companies are a mixture of software, analytics and hardware companies. According to **Comet Labs**, a VC fund that invests solely in AI and robotics, the main components that power AI in agriculture are the following in order of total percentage represented:[59]

- **Data Analytics (35%) -** Monitoring and processing of sensor data into actionable recommendations.
- **Machine Perception (24%) -** Includes a range of sensors such as hyperspectral imaging, LiDAR, and NDVI.
- **Sensors (19%) -** Includes temperature, humidity sensors, and other soil sensors.
- **Robotics (14%) -** Driverless tractors, drones, smart farm machinery, and associated robots.
- **Algorithms (5%) -** Includes natural language processors and behaviour adaptive based solutions.
- **Admin Tools (3%) -** Farm management software and cloud enabled systems that report on the execution or results of an automatable task or production plan.

[59] https://blog.cometlabs.io/meet-some-of-the-startups-transforming-agriculture-with-robots-and-ai-4a482daf119c

MARKET DRIVERS AND TRENDS

The growing volumes of biomedical and health care patient data have driven much of the healthcare and drug discovery interest in AI. In combination with the availability of significantly more powerful computational solutions, the trend for development of learning algorithms to navigate large volumes of data are driving AI approaches in these industries.

In conjunction with the AI market, the big data analytics environment is projected to grow to $43.3 billion by 2023,[60] with big data storage and on-demand deployment making up the largest segments. AI solutions are expected to grow off the back of this market.

HEALTHCARE

The key challenges underlying the need for AI solutions in the healthcare sector, which are driving adoption include:

- the need to analyse vast quantities of data in less time;
- the need for tools to aid clinician workflows with decision support systems,
- the need for solutions for cost savings
- the need for improved patient outcomes.

Some specific needs across healthcare include: analysing unstructured data, data privacy, the cost of prescription drugs and nursing shortages.

The principle driver of AI to tackle these market challenges and needs are the excellent treatment outcomes emerging from various global studies demonstrating the positive outcomes and cost reduction resulting from the use of AI as decision support tools – in particular demonstrating a drastic reduction in diagnostic and treatment costs. Hospital-based studies have shown a 30-50% increase in positive patient outcomes at roughly 50% of the cost.[8] This will likely further increase demand among hospital management and patients alike.

A broader healthcare trend for personalised medicine and more individual treatment plans which cater to patients' specific genetics and needs is driving a more evidence-driven decision-making trend by care providers.

The cost and efficiency savings emerging from adoption of these smarter AI systems have begun to be demonstrated. Healthcare systems such as **NHS England** have developed plans to invest in AI, encouraging its application in medicine and the health service. For the NHS a key benefit is the task of analysing large amounts of patient symptom information and the vision of making smarter diagnoses, even prior to symptoms being displayed.[61] The challenge around AI adoption for a healthcare system such as the NHS will be institutional readiness and coordinated introduction. Commitment from management teams to

[60] https://healthitanalytics.com/news/artificial-intelligence-in-healthcare-market-to-see-40-cagr-surge

[61] https://www.theguardian.com/society/2017/sep/12/patients-illnesses-could-soon-be-diagnosed-by-ai-nhs-leaders-say

understanding and utilising AI solutions is however a promising first step in driving adoption in national healthcare systems.[62]

The communication about the use of AI platforms in a clinical setting as decision support tools, rather than decision-making tools, will help to drive uptake of AI in healthcare systems. Furthermore, the use of big data in the healthcare setting and cognitive analytics is expected to be used for re-designing reimbursement models in the pharmaceutical and healthcare industries. There is a patient-centric trend across the industry and a shift towards fee for value in the space which extends to the drug discovery market described below.

DRUG DISCOVERY

The key challenges underlying the need for AI solutions in drug discovery for the pharmaceutical industry include:

- Cost of developing prescription drugs
- Timeline for developing prescription drugs
- The failure rate of drugs entering clinical trials

The industry's willingness to consider AI approaches reflects the industry reality that drug discovery is laborious, time consuming and not always effective, with high attrition rates. Estimates suggest that 10% of drugs entering phase I clinical trials will reach the patient.[17] Half of these clinical trial failures are attributable to a lack of drug efficacy, suggesting that the targets are not optimal candidates from pre-clinical work.

A key driving force for the industry interest in AI approaches is the growth of biomedical data and, in parallel research areas, the need for fast, efficient means of analysis and identifying patterns and candidates.

Machine vision, which has been developed in the automobile industry and applied to self-driving cars, is also now used for deep learning algorithms which can be used to model biological processes from assay and text data.[57]

AGRICULTURE

The growing demand for remote sensing (in-field sensor and drone) capabilities and algorithms that can interpret environmental conditions and help farmers make more informed decisions are key factors driving the AI market in agriculture. Remote in-field sensing is expected to play a vital role in surveying the quality and yield producing, and to save significant time for farmers. Satellite imaging, image processing, 3D mapping, and spectroscopy will allow for a significant boost in in-field observations compared to conventional methods. AI systems for livestock that provide information regarding health and welfare of animals are already under investigation and are expected to drive wider adoption.

[62] https://www.theguardian.com/society/2017/sep/12/patients-illnesses-could-soon-be-diagnosed-by-ai-nhs-leaders-say

Finally, automated irrigation systems, powered by AI, which enable farmers to reduce production costs, and increase sustainability will create big growth opportunities for the AI market in agriculture.

North America and Europe will witness greater demand for AI solutions in agriculture due to their robust technology infrastructure. However, the market is expected to undergo its highest growth rate in the Asia-Pacific region. This is due to vast opportunities in upgrading the traditional and outdated agriculture industry in the region.

BARRIERS TO ENTRY

There a number of issues with AI as a novel tool for increasing the efficiency of the sectors described. These are outlined in the Table below. A key overall issue will be the deployment of such a disruptive technology into well-established infrastructures, such as healthcare delivery organisations. Gaining acceptance and enhancing human worker-computer interaction to integrate AI into these sectors will be crucial to its further penetration.

Barrier	Description	Industry Sector		
		Healthcare	Drug Discovery	Agri-tech
Data	Deep networks demand computational power, which as adoption increases will likely need to become increasingly more powerful and sophisticated.	✓	✓	✓
	In parallel to the increasing volumes of data generated in the era of big data and cloud computing functioning to feed AI solutions, for AI to truly prosper, data ownership and access remain barriers. For example in drug discovery, the technology progression depends on widespread access to data from big pharma owners (>30 years of data collection) and patient records which make privacy and security key market issues.	✓	✓	
	Clean and accurate data availability are key. Good quality data is essential for the accuracy of AI systems. This can be a big challenge in some sectors (e.g. healthcare). For agriculture AI solutions can be problematic where automated decision tools are built on incomplete data sets.	✓	✓	✓
	Large data requirements are required to train AI algorithms. There is significant spatial data in agriculture but most is available only during the growing season. In addition agriculture as a field is not consistent with recording detailed historical data. Therefore this will take time to generate and collect effectively.			✓
Technology	Generating insights from unstructured data such as physician-entered notes, images, blogs, reviews, social media and data from mobile devices or apps will be a key focus for technology development and may hamper fast	✓	✓	

Barrier	Description	Industry Sector: Healthcare	Industry Sector: Drug Discovery	Industry Sector: Agri-tech
	adoption.			
	The development of AI solutions in the life sciences requires specialist expertise and programmers capable of technology development as well as bioscience or healthcare knowledge	✓	✓	✓
Ethical issues	Physicians and clinicians have concerns that AI could replace their expert opinion and jobs, which may restrict adoption. Such cultural issues may be difficult to overcome. The value that machine learning and AI can bring to the work of biologists and clinicians will need to be communicated and fully understood.	✓	✓	
	Evidence suggests a personal, human connection is essential to improve overall patient health, irrespective of the AI-based data the physician has access to.	✓		
	Consumers and patients have concerns about the impact of AI data	✓	✓	✓
Efficacy	For AI to truly dominate the biopharmaceutical industry, the technology will need to deliver marketable treatments and improve on attrition rates. To date bioinformatics analysis has not had a significant impact on failure rates, which makes big pharma wary.[57]		✓	
	AI applications are expected to improve and have a bigger impact as more farms join in and more data become available. With the general hype surrounding Digital Farming, Big Data and AI farm data is becoming both more rich and robust. The estimated amount of data generated by the average farm per day is expected to grow exponentially and grow from essentially zero in 2010 to more than 500,000 data points per day by 2020, and in excess of 4,000,000 by 2034.[63],[64]			✓
Cost	The cost of each data point in the pharmaceutical industry is very high. This highlights a need for AI algorithms which don't need huge datasets to generate reliable leads	✓	✓	

[63] For example, Slantrange, a San Diego-based start-up, developing a machine vision system to measure crop populations and detect weeds. When originally deployed in the field (South Africa), the company's plant counting algorithm did not perform as expected mainly because the algorithm was trained with data from a different location (different planting densities & soil composition). The updated the algorithm with the new data, this version of their system was re-deployed only two days after the original test with success. The company recently announced a partnership with Bayer Crop Science to aid in plant breeding.

[64] http://uk.businessinsider.com/internet-of-things-smart-agriculture-2016-10

Barrier	Description	Industry Sector		
		Healthcare	Drug Discovery	Agri-tech
	(drug compounds or biomarkers etc.)			
	The majority of farms lack the necessary information technology infrastructure, connectivity and data storage capabilities. These will need to be upgraded significantly and become more robust before AI solutions can be successfully deployed in agriculture.			✓
Institutional Readiness	To realise the value of AI, particularly in the healthcare sector, players such as the NHS need to incorporate AI expertise into the organisational structure and governance. Healthcare systems between countries are diverse and complex, penetrating these institutions and gaining acceptance will be challenging for the field.	✓		
	Largescale implementation of AI systems is needed for efficient adoption in healthcare systems. Precision and improvements in AI systems are gained through more data and experience in a given field thus efficacy outcomes will depend on uptake.	✓		
	AI and connected devices represents more complexity for farmers. The majority of farms lack the necessary information technology infrastructure, connectivity and data storage.			✓
Existing players	Google Brain, the deep learning project for Google is a growing key player in the biosciences application of AI. The company has been aggressively hiring AI experts globally. Many experts suggest that Alphabet (Google's parent company) will spin-up an AI powered drug discovery company in the near future		✓	
	There are questions as to whether biotech companies, especially smaller ones, will be able to optimally access AI technologies.[6]	✓	✓	
	A lack of standards, poor transparency around data use and ownership, as well as the difficulty of gathering and sharing data exacerbate the situation for developers who have limited data. Initiatives such as the Climate Corporation's FieldView Drive, John Deere's JD Link, and Farmobile's PUC aim to make the collection and transfer of data faster and easier.			✓
Regulatory	AI solutions in healthcare muddy the distinction between making recommendations and making decisions, which could lead regulatory bodies such as the FDA to regard the systems as medical devices and subject them to regulatory scrutiny, which would be more costly and time-consuming for development.	✓		

RESEARCH LANDSCAPE

A number of academic laboratories are developing AI technology, for application to the life sciences. Indeed, many of the patent filings in the neural networks and deep learning space, across all industries, are filed by academic institutions: 40% of assignees filing in 2016 are classified as either a university or research institute.[65]

The key research areas and academic sub-disciplines involved in the development of AI solutions include the following:

- Machine Learning (forms the foundation of AI)
- Deep Learning (subfield of machine learning concerned with algorithms inspired by the structure and function of the human brain)
- Computer Vision/ Image Recognition
- Natural Language Processing (NLP)/ Speech Recognition
- Cognitive Computing
- Robotics
- Data Mining
- Support Vector Machine
- Social Media Analysis
- Knowledge Representation and Reasoning (KRR)

While this is list is not exhaustive, it captures the majority of technology sub-disciplines of AI in which research is currently taking place. Despite the wide range of published articles regarding the commercial promise of AI and industrial adoption, academic research is rarely analysed. Nevertheless, scrutiny of academic research is useful, in that it can serve as a good indicator of what industry will do next, as well as offering a snapshot of where the market stands now.

The past decade has been particularly interesting, with substantial progress in the field of AI, algorithmic analysis and real-world applications. Current trends and market projections, suggest that AI is expected to be one of the main drivers for the digital transformation of industries worldwide.

However, it is also worth noting that some commentators have voiced concern about the more subtle impacts of industrial migration, which leaves universities temporarily devoid of top talent, and could ultimately sway the field towards commercial endeavours at the expense of fundamental research. Indeed, most of the top tech firms in the AI field employ many ex-university researchers, drawn to private firms' superior computing resources and salaries.[66]

[65] http://www.clearviewip.com/ip-artificial-intelligence-market/

[66] Giney (2016) *AI talent grab sparks excitement and concern*. Nature, **532**, 422–423

ACADEMIC PUBLICATIONS SEARCH

We have carried out literature searches to get an idea of the level of research currently taking place, the most prevalent topics, and the number of publications in the field of AI.

To generate a list of published papers that focus on AI research, databases were searched using the following broad technology search terms:

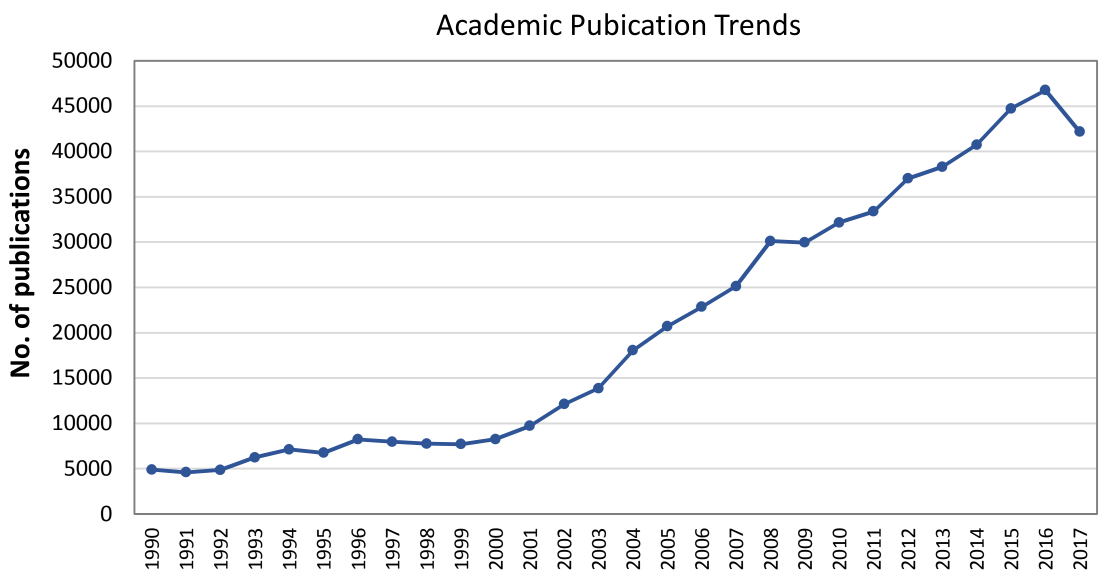
Article Title, Abstract, Keywords: ***((artificial AND intelligence) OR (machine AND learning) OR (natural AND language) OR (deep AND learning) OR (pattern AND recognition) OR (cognitive AND computing))***
Publication period: ***Jan 1990-Nov 2017***

As with the patent search discussed later, keywords were chosen to represent the AI technology areas currently dominating the research field. Additional relevant keywords such as "robotics" and "big data" were considered sub-topics and hence not included. Common acronyms such as "AI" could not be included due to the high number of spurious results returned.

The search results yielded 621,998 publications across all subject areas. These results are analysed and discussed briefly in the following sections.

PUBLICATIONS BY YEAR

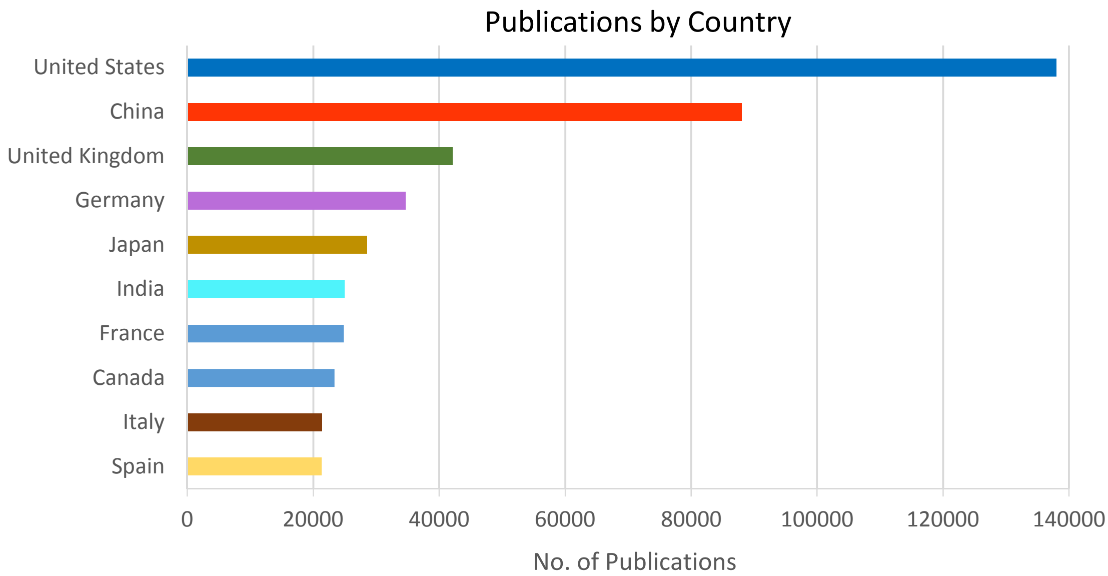
Publications by year offer a snapshot of the activity trend in this particular research field over a given time period. The search identified all the relevant publications for the last 27 years.



The annual trend points to a consistent increase in the number of publications for the period under investigation. AI-related publications started increasing significantly from 2001 onwards, reaching a historic peak in 2016 with 46,764 publications. Data for 2017 are not yet complete, which accounts for the drop at the end of the trendline.

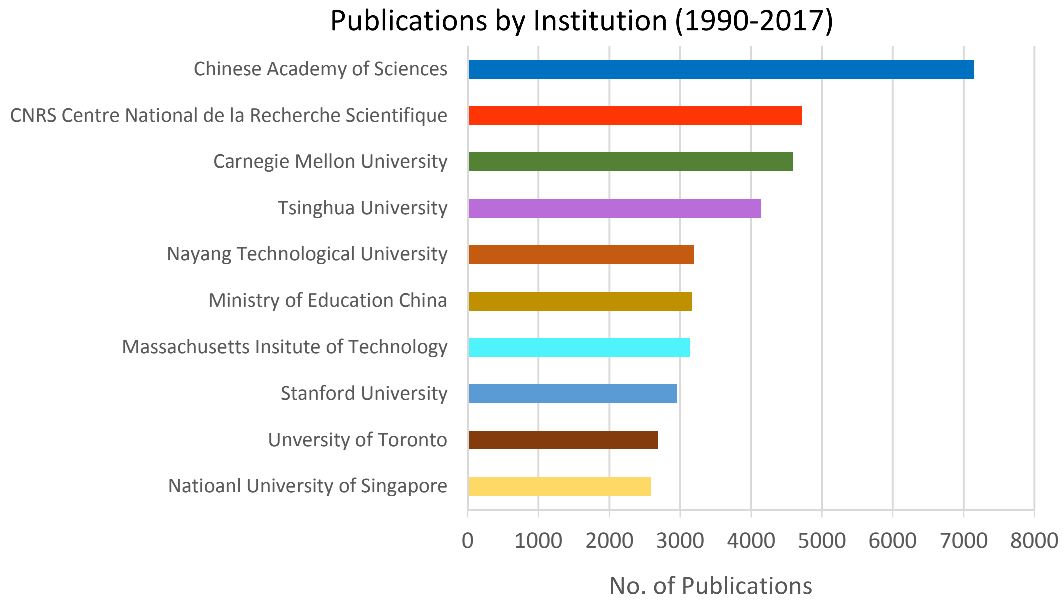
PUBLICATIONS BY COUNTRY

According to our searches, more than 70 countries are active in AI research. As shown in the graph below, the most active countries in terms of frequency of publication in descending order are the United States, China and the United Kingdom, followed by Germany, Japan, India, France, Canada, Italy and Spain. The fact that the most developed countries are leading the field and produce more publications is not surprising considering the number of research institutes and the dollar amount of research funding in these countries. These results align with the geographical analysis of the patent search and deal flow, which further substantiates the conclusion that the majority of innovation in the field of AI comes from the United States and China, followed by Europe.



PUBLICATIONS BY AFFILIATION

Focusing on the most prolific publishing organisations in the field of AI research allows us to determine the comparative level of activity in this space. The analysis is based on the number of publications across different disciplines assigned to each institution. Plotting the number of publications by affiliation demonstrates that, although collectively the United States displays the highest number of publications, the **Chinese Academy of Sciences** has the highest number or AI-related publications (7,152 publications). The list of the top 10 institutions is completed by the **Centre National de la Recherche Scientifique** (FR), **Carnegie Mellon University** (US), **Tsinghua University** (CN), **Nayang Technological University** (SG), **Ministry of Education China** (CN), **Massachusetts Institute of Technology** (US), **Stanford University** (US), **University of Toronto** (CA), **National University of Singapore** (SG).



As expected, the US and Chinese institutions have the strongest representation, while Singapore accounts for a significant amount of research with two institutions in the top 10. Nevertheless, this evaluation should consider the quality of research output. A recent report by Clarivate Analytics,[67] analysing citations by country, argues that the volume of research and quality of research don't necessarily align. According to the report Asian countries such as China, Japan and Korea, have a significantly lower research impact than the United States and relatively lower impact than European countries. The immediate conclusion is that although Asian countries commit significant resources towards AI research, their global impact is, for the time being, more limited.

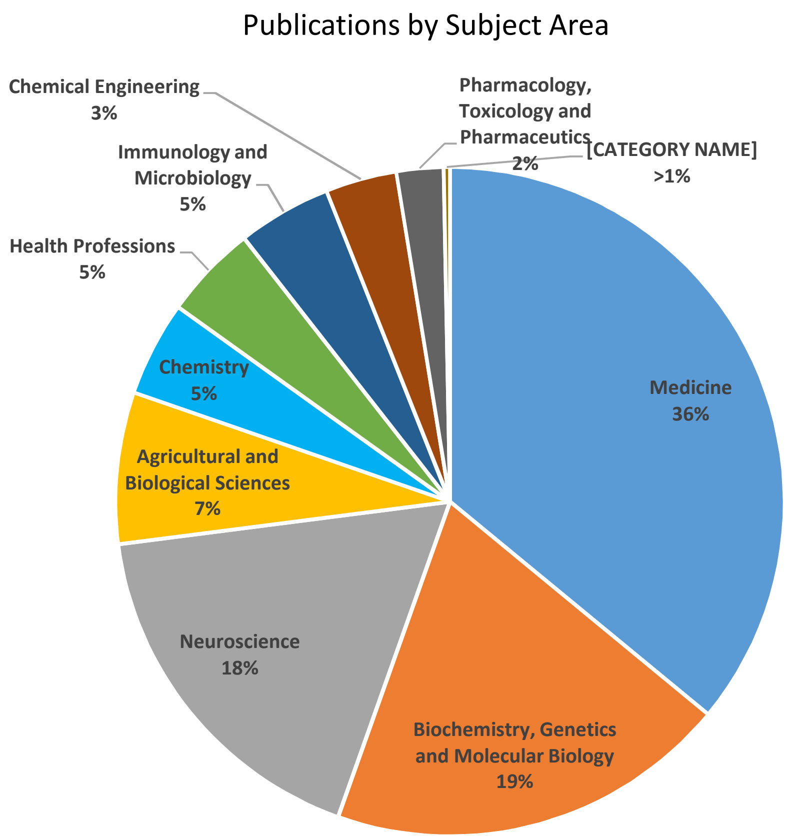
PUBLICATIONS BY SUBJECT AREA

An analysis of the number of publications by subject area, makes an assessment of the research fields which have been the most prolific in terms of AI. The subject areas of Computer Science, Engineering and Mathematics were the most populous with 376,859, 164,474 and 134,046 publications respectively for the period under investigation (1990 to 2017). This result is not surprising as these three academic disciplines form the scientific basis of AI technologies.

To identify the publications that relate to life sciences, healthcare and agriculture, the search was limited by subject area to: Medicine, Biochemistry, Genetics and Molecular Biology, Neuroscience, Agricultural and Biological Sciences, Chemistry, Chemical Engineering, Health Professionals, Immunology and Microbiology, Pharmacology, Toxicology and Pharmaceutics, and Veterinary. Approximately 36% of the initial 621,998 publications fall within this narrower search. As shown in the chart below, the majority of the publications relate to medical and healthcare fields such as Medicine, Neuroscience, Biochemistry, Genetics and Molecular Biology. Agricultural and Biological Sciences account only for 7% of the AI

[67] *Artificial Intelligence – The innovators and disruptors for next generation digital transformation*, Clarivate Analytics (2017)

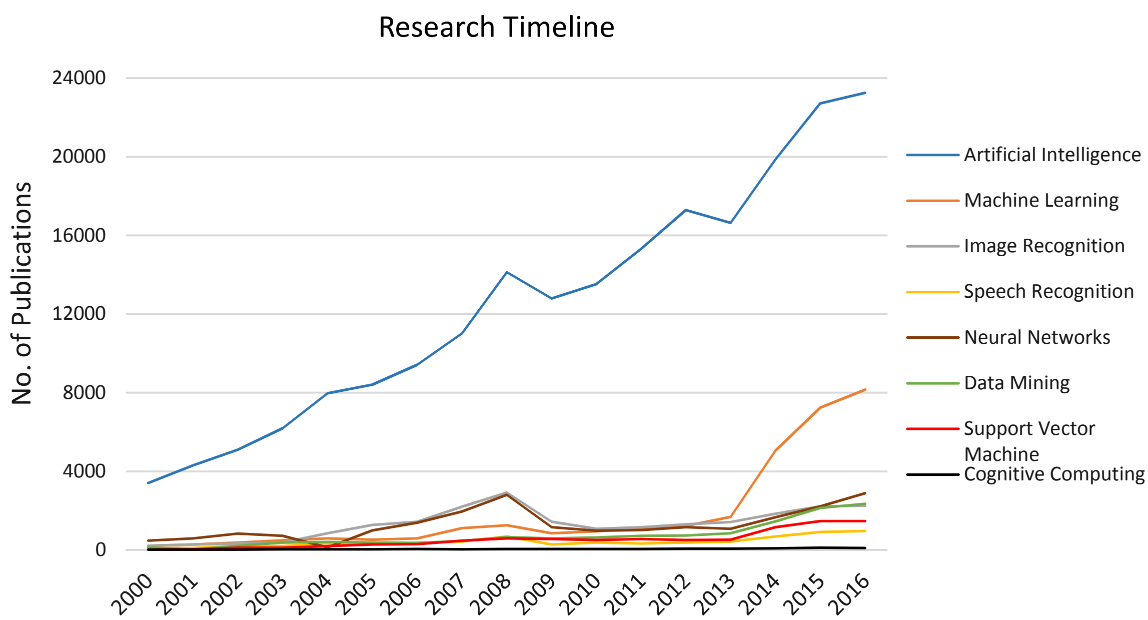
academic research in the life sciences, healthcare and agriculture space. Broadly speaking, this is also reflected in the activity levels described in the market and deal flow sections of this report.



An analysis of the most prevalent keywords as identified by the searches is indicative of the type of research that is currently carried out. To ensure that the keywords refer to the latest type of research, the original broad search was limited to the past decade and hence only publications from 2007 onwards were included. The list of the most prevalent keywords along with the number of publications associated with them is given in the following table.

Keywords	No. of Publications
Pattern Recognition	63,666
Learning Systems	53,539
Machine Learning	29,941
Neural Networks	26,470
Natural Language Processing Systems	23,486
Learning Algorithms	22,626
Data mining	20,089
Feature Extraction	19,709
Semantics	18,529
Image Processing	16,649
Pattern Recognition, Automated	15,848
Pattern Recognition, Visual	14,629
Non-human	13,855
Decision Support Systems	13,580
Decision Making	13,430
Computational Linguistics	13,139
Computer Vision	12,420
Support Vector Machine	10,510
Information Retrieval	9,435
Artificial Neural Network	8,908
Linguistics	8,805
Face Recognition	8,762
Image Segmentation	8,734
Image Analysis	8,330
Genetic Algorithms	8,145
Computer Assisted Diagnosis	7,639
Image Interpretation, Computer Assisted	6,847
Robotics	6,239
Speech Recognition	6,150
Human Computer Interaction	5,893
Cognition	4,733

Some of the key topics and methods in the field of AI were plotted against time in an attempt to look at their evolution and generate a research timeline (see graph below). Data for 2017 were not included given that they were incomplete at the time of publication and could potentially display a false decreasing trend.



Note: (a) Machine learning includes publications in the field of Deep Learning. (b) Image Recognition includes publications associated with Computer Vision, Image Processing, Image analysis, and Image processing. (c) Speech Recognition includes publications related to Natural Language Processing (NLP).

Although AI research has increased dramatically over the past decade, most of the sub-fields have been evolving at a slower pace. It is clear from the above graph that Machine Learning is at the forefront of AI research and is attracting significantly higher attention by the academic community, and possibly industry, compared to the remaining fields described.

Research started picking up from 2004 onwards, with the fields of Image Recognition and Neural Networks exhibiting strong growth and reaching a peak in 2008. However, these two fields experienced a 'winter' of innovation for the following five years (2008 to 2013) with publications decreasing by more than 50% for both fields. Since 2014, research in both fields has experienced a renewed enthusiasm with publication numbers recovering.

With a closer look it is also noticeable that besides Machine Learning, Data Mining and Support Vector Machine are also fast growing topics/methods. Publication numbers suggest that almost half of the total research revolving around Data Mining and Support Vector Machine has been produced in 2014, 2015, and 2016 (47% and 46% respectively). If we were to include data for 2017 (although incomplete) the respective percentages would exceed 55% for both fields.

The progress of Data Mining related research is not surprising when taking into account the general hype surrounding Big Data and the wealth of unstructured data becoming available on a daily basis. The field of Support Vector Machine is likely propelled by its connection to Machine Learning and the progress recorded in this field.

Governments and industry alike are partnering with academic institutions focused on AI to extract the commercial and economic potential. Several initiatives are described throughout the report, but some examples in the life sciences include:

- The Japanese government launched a research consortium centred on using Japan's K supercomputer to increase drug discovery efficiency across >20 local companies and institutions. Among those involved are **Takeda** and technology corporates such as **Fujitsu** and **NEC**. In parallel, **Kyoto University Hospital** and **Riken**, Japan's National Research and Development Institute, provide clinical data to support the initiative.

- The Cancer Moonshoot Initiative in the US, is another example of industry and academia collaborating to apply AI to accelerate drug discovery.
- The Accelerating Therapeutics for Opportunities in Medicine (ATOM), launched in January 2016, marries computational and experimental approaches. **GSK**, the **Lawrence Livermore National Laboratory** in California and the **US National Cancer Institute** are involved. The computational technology includes deep-learning and other AI algorithms, will be tested with the aim of delivering a drug candidate.
- **Atomwise**, originally a **University of Toronto** spinout, now based in San Francisco, launched an AI screen tool called AtomNet in 2017 which aims to deliver therapeutic compounds for a specific target of interest, to approx. 100 university research institutions for further research and development activities. The company also has an alliance with **Merck**.
- Genomics data analytics start-up **WuXi NextCode Genomics** of Shanghai; Cambridge, Massachusetts; and Reykjavík, Iceland, collaborated with researchers at **Yale University** on a study that used the company's deep-learning algorithm to identify a key mechanism in blood vessel growth. The result could aid drug discovery efforts aimed at inhibiting blood vessel growth in cancerous tumours.

PATENT ANALYSIS

OVERVIEW OF GENERAL AI PATENTING

Several recent reports have shown that patenting in AI research is an extremely active area.[11,65,67] In December 2016, **Google** and **Elon Musk** opened their AI platforms to the public,[68] **Uber** launched Uber AI Lab[69] and **Apple** announced that for the first time it will publish their AI research.[70]

There is significant interest in the future applications for AI and there are a lot of interwoven technologies advancing in parallel, such as robotics, virtual reality, autonomous vehicles, blockchain, 3-D printing and the IoT.[62] There is fierce competition for ownership and leadership amongst the top companies which is helping to push AI innovation forward and accelerate advancements in current and future applications.

Technology giants such as **Google**, **IBM**, **Microsoft**, **Intel**, **Facebook**, **Amazon**, **Baidu**, **Samsung** and **Apple** have been patenting heavily, and, along with industrial multinationals across industry sectors such as **Boeing** and **GE**, have been racing to acquire AI start-ups.[71]

The deep learning technology sub-sector is currently propelling AI patenting activity as well as investment activity.[72] Deep learning is a form of machine learning in which neural networks are fed information that is used by a computer to make decisions, train itself and adjust based on what it has learned within specific parameters.[62]

Despite the prominence of the largest global tech firms, the innovation landscape is remarkably diverse. Much of the more recent research is coming from academic sources, with 40% of patent assignees filing in 2016 being an academic/research institute. An even larger number of patents are filed by smaller companies outside the top 50 most common assignees.[62]

Unsurprisingly, computing, data processing, and sensor technologies comprise the bulk of the patents filed over the last five years, with applications predominantly in transport (e.g., self-driving vehicles, traffic congestion, airport security) and telecommunications. Other filing areas include energy, agriculture, gaming, medical technology, manufacturing and nanotechnology.[62]

[68] https://www.inc.com/kevin-j-ryan/elon-musk-google-open-source-artificial-intelligence-platforms.html

[69] https://www.uber.com/newsroom/ailabs/

[70] https://www.theverge.com/2016/12/6/13858354/apple-publishing-ai-research-siri-self-driving-cars

[71] https://siliconangle.com/blog/2016/11/15/ge-adds-ai-and-industrial-iot-startups-to-its-list-of-acquisitions-this-week/

[72] https://venturebeat.com/2016/04/02/deep-learning-will-be-huge-and-heres-who-will-dominate-it/

PATENT SEARCH

In order to understand the AI intellectual property landscape across the healthcare, drug discovery and agriculture spaces specifically, an assessment of the registered industrial patent rights was carried out using Derwent Innovation, a global comprehensive patent database. A broad search was conducted using the following search string within the Title/Abstract/Claims (CTB) of any patent:

CTB=((artificial ADJ intelligence) OR (machine ADJ learning) OR (natural ADJ language) OR (neural ADJ net) OR (deep ADJ learning) OR (cognitive ADJ comput*) OR (pattern ADJ recognition) OR (data ADJ mining)) AND AD>=(20071109) AND AD<=(20171109) AND IC=(A61* OR A62* OR A9*OR OR G6* or A01*);*

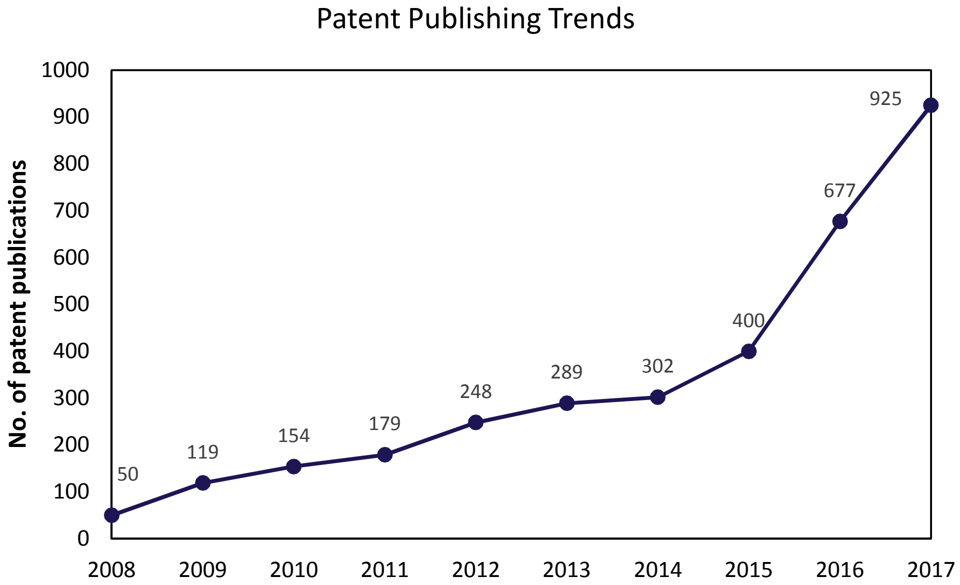
These keywords were chosen to represent the AI technology areas currently dominating the research field. Other relevant keywords such as “robotics”, “big data” or “speech recognition” were considered sub-topics of the above fields and will be discussed in more detail later. Common acronyms such as “AI” could not be included due to the high number of spurious results returned. The patent search was limited to patent applications published in the AI space over the last 10 years. To identify the most relevant patent set for healthcare, drug discovery and agriculture/agritech, the search was limited by International Patent Classification (IPC) categories: A01 (agriculture; forestry; animal husbandry; hunting; trapping; fishing); A61 (medical or veterinary science; hygiene); A62 (life-saving; fire-fighting); A99 (subject matter not otherwise provided for in human necessities) and G06 (computing; calculating; counting).

The search pulls data from all available patent authority collections within the database, including the full patent text for: US Granted; Australian Innovation; Canadian Granted; German Granted; US Applications; Australian Granted; Canadian Applications; German Applications; European Granted; Australian Applications; French Granted; European Applications; UK Granted; French Applications; WIPO Applications; UK Applications; German Utility Models. In addition, the bibliographic data for: Japanese Applications; Korean Granted/Examined; Korean Applications; Other Authorities. In addition, the Derwent Innovation proprietary DWPI data fields were searched for these selected collections.

The resulting search identified 8316 patent records filed in the 10 years from November 2007 to November 2017. These cases make up 3343 INPADOC patent families with which we have conducted the patent analysis below.

PATENT PUBLISHING TRENDS

Patent publishing trends offer a snapshot of the level of activity in the space over the given period. This filing data gives an indication of the number of new inventions published in AI for healthcare/agriculture over the course of the past 10 years. Derwent Innovation uses the publication number to include both published application numbers and granted patent numbers.



There was a steady increase in patent filings for AI applications in the key areas of interest from 2008-2014, followed by a sharp increase over the last two years. This is unsurprising given the rapid advancements in big data, neural networks, parallel processing and cloud technology which has occurred over a similar time frame. AI technologies are just now becoming mainstream, because the hardware and processing technology has caught up with the vision. The critical mass of data needed to "teach" computers now exists and the storage and processing power to execute deep learning are available, fast, and cost-effective.[62]

KEY ENTITIES

Focusing on the top organisations filing in the sector allows for identification of those organisations carrying out R&D in the area and the comparative level of activity in the space. The analysis is based on the number of patent publications assigned to them in the broad dataset. The data shows a market dominated by large multinationals. **Philips** and **Siemens** (including **Siemens Healthcare** and **Siemens Medical Solutions**) are by far the most prolific patent filing organisations, followed by a number of large companies with a similar level of patenting activity. There are also a number of U.S. and China-based academic institutions featured, including the **University of California**, **MIT**, **Tianjin University and Zhejiang University**.

CLUSTER BY ENTITY TYPE: COMMERCIAL VS. ACADEMIC

The top patent publishing organisations were divided into commercial companies and academic research institutions. The table below summarises the top commercial organisations in order of patenting activity, and their key areas of interest. Some of the key applications of AI technology are based on medical imaging/analysis and image-based detection methods. It is therefore unsurprising that companies operating in computing, electronics and/or imaging represent the majority of patents. This field is dominated by **Koninkl Philips** and **Siemens**, who hold 225 patent families between them in the research areas outlined in the table.

Other notable players include **Samsung**, which has a number of patents based on the methods/apparatus for medical measurements, data processing and surgical robotics. Examples include EP3215021A1 (*Medical image processing apparatus and method*), which describes medical image processing apparatus using machine learning to detect image landmark positions, and US9687301B2 (*Surgical robot system and control method thereof*), where machine learning of the plurality of motions of a robot system is used in the control system.

IBM holds notable patents such as US8594398B2 (*Systems and methods for cardiac view recognition and disease recognition*) which uses a neural network classification system for recognising heart disease in a cardiac echo video, and US9002773B2 (*Decision-support application and system for problem solving using a question-answering system*) which describes generating natural language queries from electronic medical records and providing corresponding decision support for medical professionals.

GE has patents in similar areas to those given above, such as US20170098047A1 (*System and method for clinical decision support*) and US9277902B2 (*Method and system for lesion detection in ultrasound images*).

Commercial Assignee/Applicant	No. of patent publications, 2007-2017	Research Interests/ Sector
KONINKL PHILIPS NV	114	diagnostics, clinical question answering, clinical paraphrasing, human-like conversational agents and automated caption generation for medical images
SIEMENS AG (including SIEMENS HEALTHCARE and SIEMENS MEDICAL SOLUTIONS)	111	diagnostics, data integration, robotics, comprehensive databases, and automatic recognition of patterns and regularities in data
SAMSUNG ELECTRONICS CO LTD	27	voice/image recognition, translation, autonomous driving, and robotics
GEN ELECTRIC	23	big data from industrial devices, IoT, digital twin, GE Health Cloud
IBM	23	robotics, medical imaging, cloud-based data analytics, data aggregation, drug discovery
TOSHIBA MEDICAL SYS CORP	20	image recognition & processing, ultrasonic diagnostics
MICROSOFT CORP (including MICROSOFT TECHNOLOGY LICENSING LLC)	18	predictive analytic tools, personal health information systems, patient monitoring,
FUJIFILM CORP	14	image recognition & processing
XEROX CORP	14	image recognition & processing, cancer detection
COVIDIEN LP	13	identifying patient distress, sound signal analysis, detection methods
HEARTFLOW INC	12	image recognition & processing, detection methods
SORIN CRM SAS	9	deep brain stimulation, neural network assembly
CARDIAC PACEMAKERS INC	9	medical device programming, heart failure prediction, automatic arrhythmia classification
MEDTRONIC INC	8	pattern recognition, condition monitoring
LMECA CO., LTD.	8	suction pumps
ZOLL MEDICAL CORP	7	cardiac events, medical devices
INTEL CORP	7	movement monitoring, intelligent agricultural systems
VOLCANO CORP	7	imaging, cardiac events
NELLCOR PURITAN BENNETT LLC	7	diagnostics

The data also identified some of the key patenting research institutions. The table below summarises each of these in order of patent publishing activity, and the location in which that research institute or university is based. All of the top institutes are based in the USA or China. The **University of California** is the most active organisation, with 38 patent families for various AI-related methods and devices for a range of applications, such as:

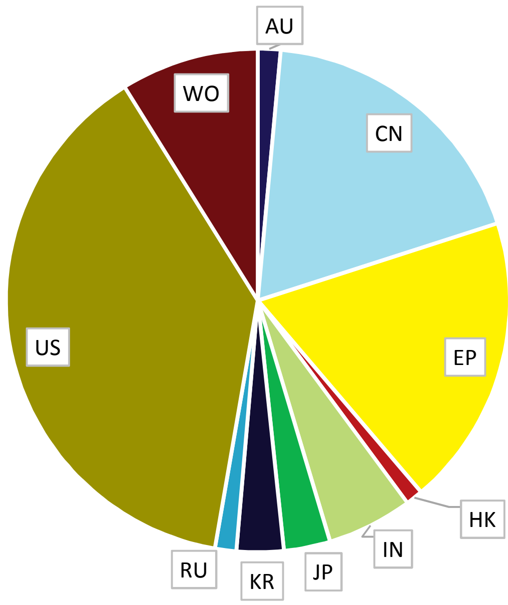
- correcting sleep apnoea using pattern recognition (US9655767B1 - *Device and method for correcting obstructive sleep apnoea*)
- computer-automated detection of implantable man-made devices, which implements machine learning techniques (US9471973B2 - *Methods and apparatus for computer-aided radiological detection and imaging*)
- evaluating infant movement using a statistical machine learning technique in the processing circuit (US9232912B2 - *System for evaluating infant movement using gesture recognition*)
- wearable sensors for a pregnant mother to extract biometric data about the fetus and analyse the data using a machine learning algorithm (US20170086709A1 - *Fetal health monitor*)

Research Institution Assignee/Applicant	Location	No. of patent publications, 2007-2017
UNIV CALIFORNIA	CA, USA	38
MASSACHUSETTS INST TECHNOLOGY	MA, USA	21
UNIV TIANJIN	China	19
UNIV ZHEJIANG (including ZHEJIANG MEDZONE BIOMEDICAL MAT AND DEVICE RES INST)	China	23
UNIV NORTHEASTERN	MA, USA	11
SHENZHEN INST OF ADV TECH CAS	China	11
UNIV JOHNS HOPKINS	MD, USA	10
UNIV TSINGHUA	China	9
HARVARD COLLEGE	MA, USA	9
UNIV SUN YAT SEN	China	9
CALIFORNIA INST OF TECHN	CA, USA	8
UNIV LELAND STANFORD JUNIOR	CA, USA	8
UNIV HANGZHOU DIANZI	China	8
UNIV TEXAS	TX, USA	7
UNIV FLORIDA	FL, USA	7
UNIV CASE WESTERN RESERVE	OH, USA	7
UNIV DUKE	NC, USA	7
UNIV NEW YORK	NY, USA	7

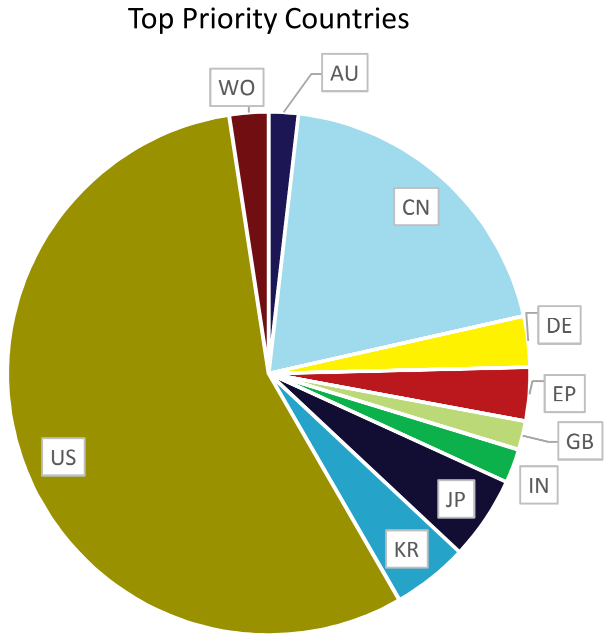
GEOGRAPHICAL ANALYSIS

The data identified through the broad patent search was analysed to identify the top countries for patent publications in the field. This gives an indication of the territories in which patent protection is sought, and is therefore an indication of those countries considered to be most important for commercialisation. Organisations will choose to publish the patent in those countries where the industry sector is likely to be most commercially viable, to secure patent exclusivity rights in those markets. Protection for AI applications in the key market sectors is sought predominantly in the US (38.4%), China (18.6%) and Europe (18.8%), which aligns with the key territories for the AI market in general. Other individual countries which are likely to be important markets include India (5.5%) and the Australasian markets of Japan (3%), South Korea (3%), Hong Kong (1.1%) and Australia (1.5%).

Top Countries for Patent Publication



This data was further analysed to identify the priority countries where the patents are initially filed. This gives an indication of where most invention is taking place, as patents are commonly filed in the home territory of the inventing company or organisation. Unsurprisingly given the filing trends described previously, the US is by far the most important territory for innovation, with 55.9% of priority filings, followed by China with 19.7%. As well as being important territories for protection, South Korea (4.7%) , Japan (5.1%), India (2.1%) and Australia (1.8%) also feature as top countries for priority filing. The UK (1.8%) and Germany (3.1%), are the most important European territories for innovation.



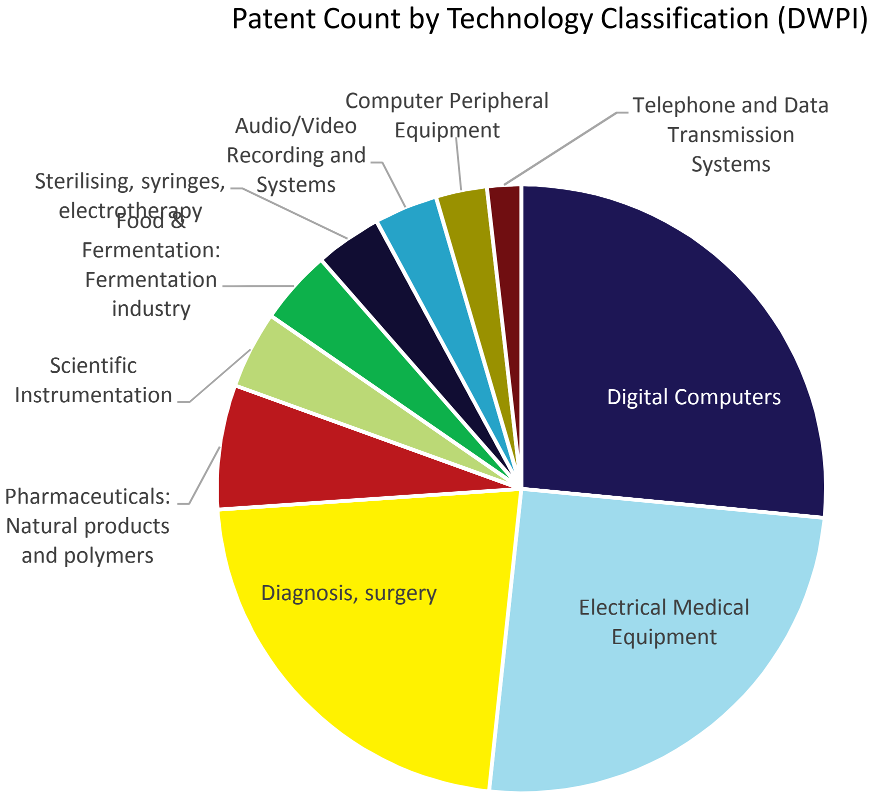
TECHNOLOGY AREAS

The patent dataset was analysed further to identify the top IPC codes within the specified IPC categories used to conduct the initial patent search. The international classification system provides for a hierarchical system of language-independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain. Therefore, these give an indication of the most important specific technology sub-areas for the AI patent landscape. Some of this can be gleaned from the top assignees as described above, which operate in key sectors such as Electronics, Computing and/or, Healthcare. However, the IPC code is the formal structure in which technologies described within a patent are classified, and so provide additional information. Below is a table displaying the top 10 IPC codes in order of commonality along with their respective description.

IPC Code	Document Count	Description
A61B000500	838	A61B – Medical or veterinary science; hygiene: Diagnosis; surgery; identification 5/00 – Measuring for diagnostic purposes.
G06F001900	402	G06F – Computing; calculating; counting: Electric digital data processing 19/00 – Digital computing or data processing equipment or methods, specially adapted for specific applications
A61B000511	237	A61B – see above 5/11 – Measuring movement of the entire body or parts

IPC Code	Document Count	Description
		thereof, e.g. head or hand tremor or mobility of a limb
G06T000700	218	G06T – Computing; calculating; counting: Image data processing or generation, in general 7/00 – Image analysis
G06K000900	201	G06K - Computing; calculating; counting: Recognition of data; presentation of data; record carriers; handling record carriers 9/00 – Methods or arrangements for reading or recognising printed or written characters or for recognising patterns, e.g. fingerprints
A61B00050476	156	A61B – see above 5/0476 – Electroencephalography
A61B000504	145	A61B – see above 5/04 - Measuring bioelectric signals of the body or parts thereof
A61B000600	143	A61B – see above 6/00 – Apparatus for radiation diagnosis, e.g. combined with radiation therapy equipment
A61B00050205	133	A61B – see above 5/0205 – Simultaneously evaluating both cardiovascular conditions and different types of body conditions, e.g. heart and respiratory condition
A61B00050402	124	A61B – see above 5/0402 – Electrocardiography, i.e. ECG

The parallel Thomson Innovation DWPI classification of the main technology areas are given in the figure and table below. The most common categories are in Computing and Control: Digital Computers (27%), Instrumentation, Measuring and Testing: Electrical Medical Equipment (25%) and general tools for diagnosis/surgery (22%). In this latter category, patents pertain to methods for image comparison, evaluation of sensor/diagnostic test performance, ranking methods, or adaptive interpretation of medical/clinical data, for instance. The dominant focus for this patent data is therefore in computational methods for analysis/monitoring/interpretation/decision-making in medical and diagnostic applications. There is little patenting in agriculture or agritech by comparison.



DWPI Class	Document Count	Description
T01	2243	Computing and Control: Digital Computers (G06C-F) Electronic data processors, interfaces and programme control. Mechanical digital computers.
S05	2127	Instrumentation, Measuring and Testing: Electrical Medical Equipment (A61, A61N) Electrotherapy. Electrosurgical apparatus. Blood cell counters. Electrical diagnostic apparatus. Tomography. Veterinary apparatus.
P31	1879	General: Health, Amusement; Diagnosis, surgery.
B04	558	Pharmaceuticals: Natural products and polymers - including testing of body fluids (other than blood typing or cell counting), pharmaceuticals or veterinary compounds of unknown structure, testing of microorganisms for pathogenicity, testing of chemicals for mutagenicity or human toxicity and fermentative production of DNA or RNA, and general compositions
S03	347	Instrumentation, measuring and testing: Scientific Instrumentation (G01J, K, N, T-W): Photometry, calorimetry. Thermometers. Meteorology, geophysics, measurement of nuclear or X-radiation. Investigating chemical or physical properties.

DWPI Class	Document Count	Description
D16	334	Food & Fermentation: Fermentation industry – including fermentation equipment, brewing, yeast production, production of pharmaceuticals and other chemicals by fermentation, microbiology, production of vaccines and antibodies, cell and tissue culture and genetic engineering
P34	299	General: Health, Amusement; Sterilising, syringes, electrotherapy
W04	284	Communications: Audio/Video Recording and Systems (G10H, G11B, H04N) Loudspeaker enclosures, cross-over networks. Audio disc recording and reproducing equipment. Audio magnetic tape recording and reproduction. Sound mixers. Electrical musical instruments. Video cameras, camera recorders, electronic still-picture cameras. Studio equipment eg video mixers, special effect apparatus. Projection TV. Video tape and disc recording and reproduction. Video games, karaoke. Electronic educational apparatus. Sports equipment. Speech coding, analysis and synthesis. Antiphase sound cancelling.
T04	229	Computing and Control: Computer Peripheral Equipment (G06K) Card and tape punches and readers. Magnetic, optical and smart cards. Serial and line printers. VDUs, character and graphics generators. Pattern recognition, magnetic ink recognition, bar coders. COM equipment.
W01	154	Communications: Telephone and Data Transmission Systems (H04L, M, Q) Error detection and correction. Code conversion. Synchronising. Secret data communication. Data networks (LAN, WAN, etc). ISDN. Baseband and broadband data transmission. Exchanges, call metering, test equipment, equipment racks. Subscriber equipment, cordless and cellular phones. Telephone line and cable installation.

PATENT LANDSCAPING

The patent search was mapped using Derwent Innovation's proprietary ThemeScape mapping tool. ThemeScape uses term frequency and other algorithms to cluster documents based on shared language – in this case the English Title, Abstract and Claims from the patent filings together with the DWPI-enhanced Titles and Abstracts. It uses several algorithms to perform terminology based clustering. The text from one record is compared with the text from all other patent records within the search collection. The map then uses vectors to give each patent record a proximity score to all of its peers. The outcome of this analysis is a visualisation of the patent space with extra patent (dot) represented once in the map. Patents in close proximity share more phraseology than those located apart. The patents are grouped into map "contours" to show areas of high and low patenting activity organised into common themes. The illustration shows these contour lines, with the "mountain peaks" representing a concentration of patents. Each peak is labelled with the key terminology concepts contained in the patents within the cluster.

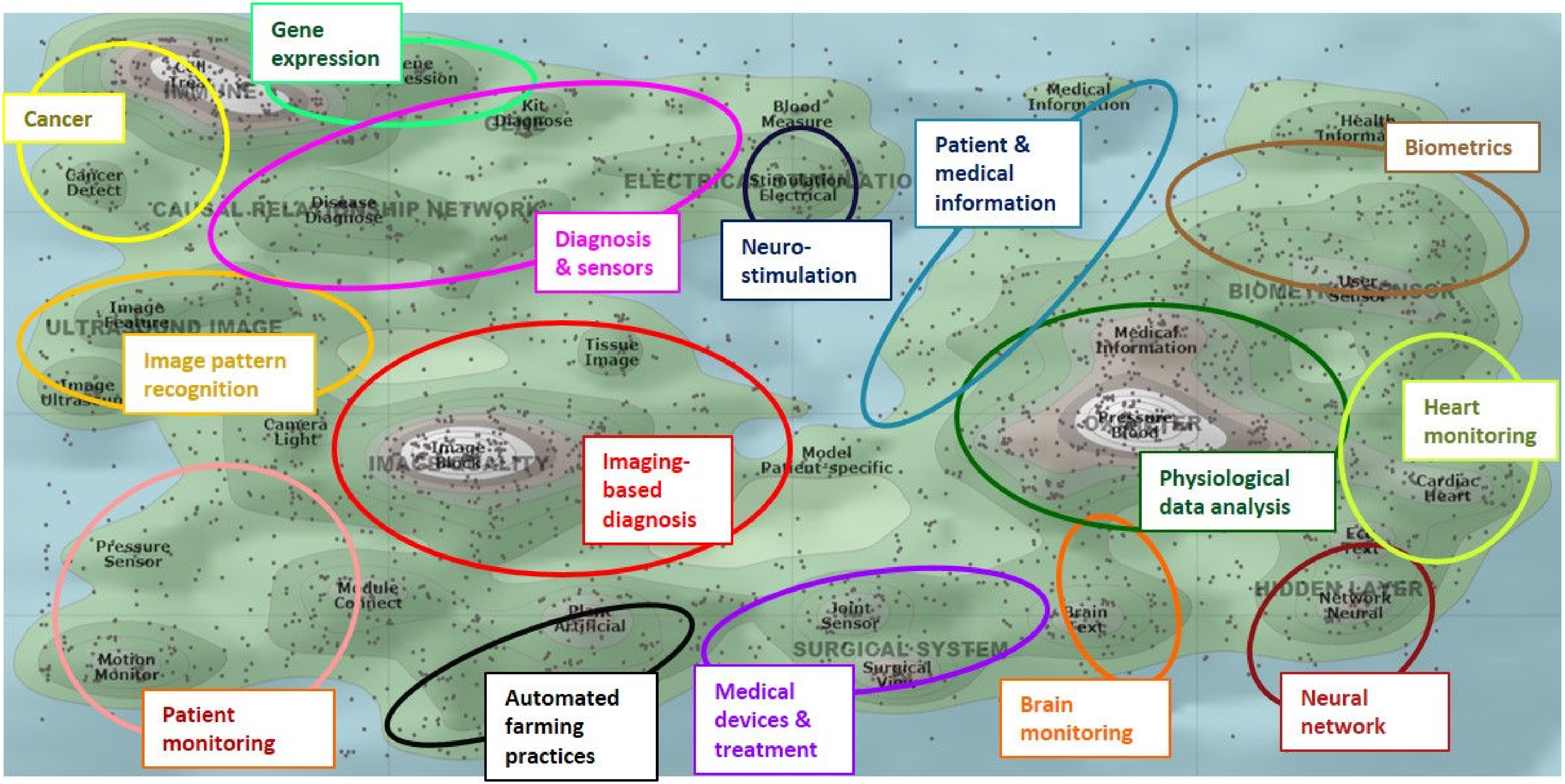
Although the landscaping is not an entirely precise tool, it is possible to identify clusters of technology areas on the map which can be useful for analysing trends within the dataset. The resulting maps from these searches are shown in the following pages.

The patent landscapes shown here reinforce the key technology areas of focus identified from initial patent searching above (i.e., computing, electronics, instrumentation and/or imaging). Though there is a high degree of crossover between these areas, Landscape 1 shows the broad applications of these technologies, which are largely in image recognition for diagnostics, sensors and biometric monitoring.

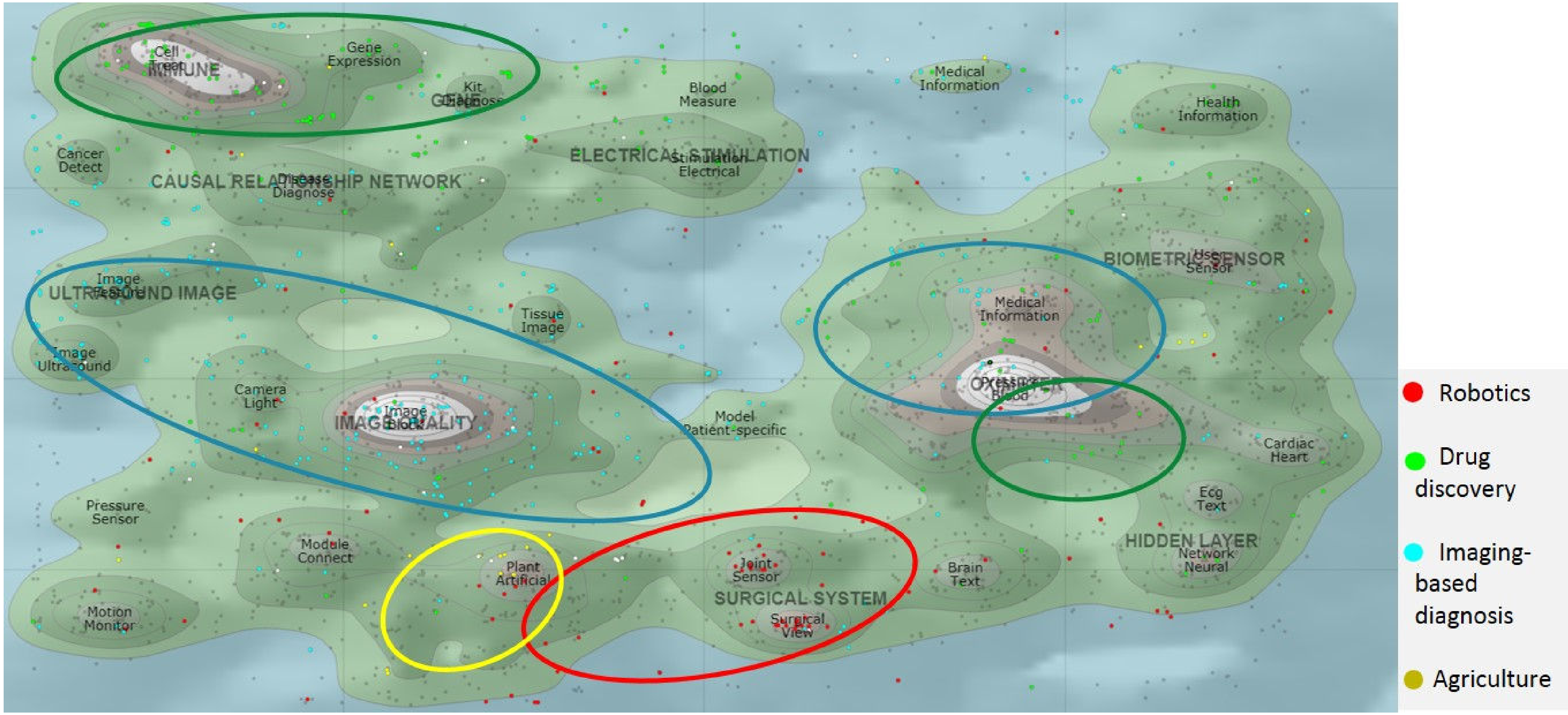
Applications of AI have been mapped further in Landscape 2 using themes identified previously in our market analysis for healthcare, drug discovery and agriculture. Specific keyword searches for robotics, drug discovery, image-based diagnosis, and agriculture/agritech are shown. Patents relating to robotics are clustered around surgical applications, in line with our finding of this as a key focus area for AI applications. Drug discovery-related patents are found mostly on the top left of the landscape, alongside cancer detection/treatment and gene expression, and on the mid-right, clustered near blood testing and general physiological data analysis. Automated image diagnosis and image-based diagnosis patents are the most common search result and are found throughout the landscape, but clustered predominantly around image analysis techniques identified in Landscape 1. Only 27 patent records were found pertaining to agriculture or agritech applications – common themes are intelligent farming equipment or predictive/modelling tools, for example:

- US8935060B2 – **Claas GmbH**'s patent titled *Driver assistance system for agricultural working machine*
- US20160378086A1 – Plymill Clayton & Norman Brett, *Control System Used for Precision Agriculture and Method of Use*
- US20170038749A1 – **Iteris Inc**, *Customized land surface modeling for irrigation decision support in a crop and agronomic advisory service in precision agriculture*

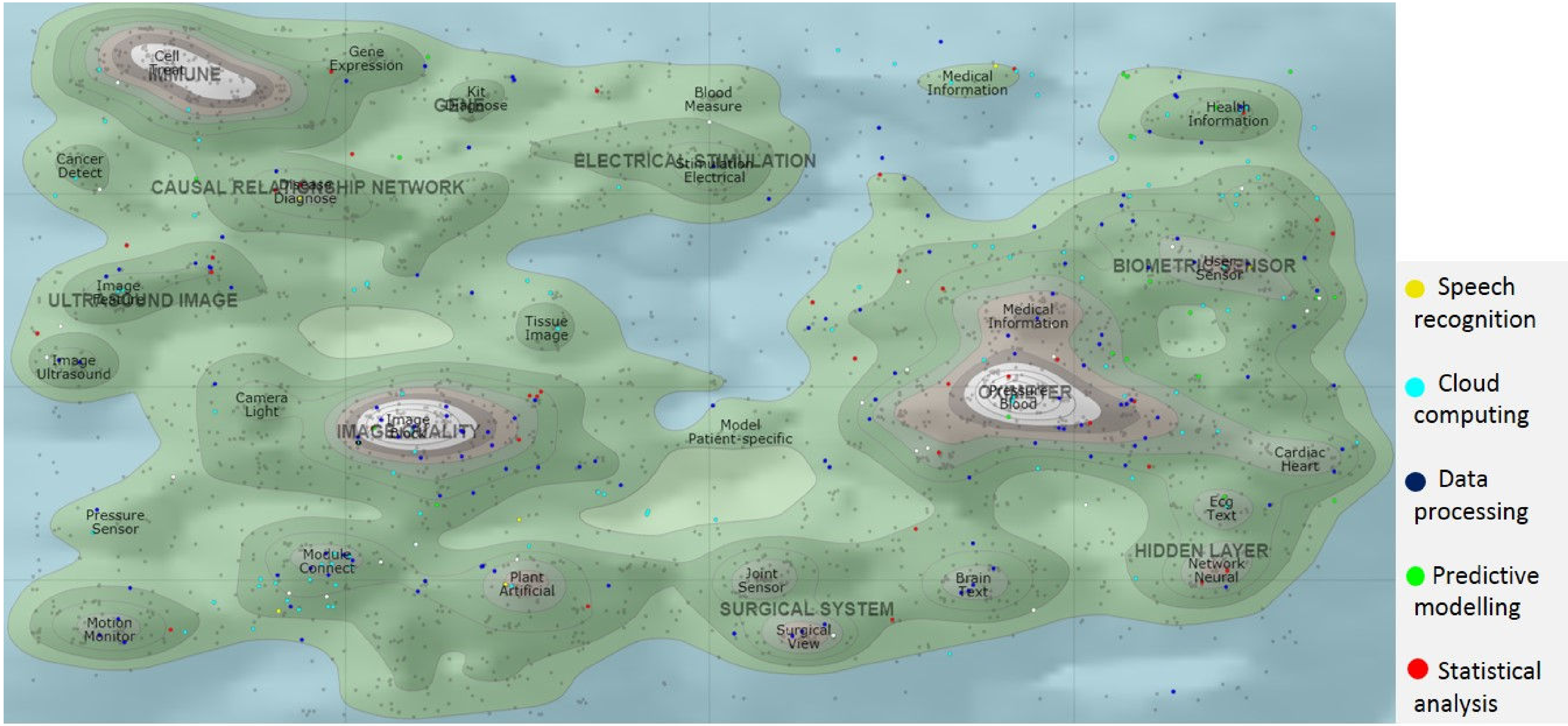
A sub-search of the patent landscape was performed to illustrate the use of other important AI-related techniques of importance, beyond the core principles included in the original search string (e.g., machine learning, neural networks etc). Patent families involving data processing, cloud computing, speech recognition, predictive modelling and statistical analysis are included in Landscape 3. As shown, patents relating to these tools are scattered throughout the landscape, reflecting the high degree of crossover between research fields and the broad applicability of such techniques to the wider AI field. Sub-searches were also performed for query interpretation and digital personal assistant, but returned no results.



Landscape 1: The landscape aims to select the broad applications of AI tools in healthcare, drug discovery and agriculture, from the search of 3343 INPADOC patent families. Applications are largely in image recognition for diagnostics, sensors and biometric monitoring.



Landscape 2: The landscape maps specific technology areas identified previously in our market analysis for healthcare, drug discovery and agriculture. Specific patent keyword sub-searches for robot*, drug*, (image* AND diagnos*), and (agricultur* OR agritech OR agri-tech) are shown.



Landscape 3: A sub-search of the patent landscape was performed to illustrate the use of other important AI-related techniques of importance, beyond the core principles included in the original search string (e.g., machine learning, neural networks). Patent families involving data processing, cloud computing, speech recognition, predictive modelling and statistical analysis are shown.

KEY PATENTS

A patent citation analysis identifies key patents and patent applications and their corresponding assignees, within a patent dataset. Citations link documents together based on the citing of one document in another. For patents this means the document has related content. In patent literature citations will either mean that the applicant has disclosed the former patent as prior art, or the examiner from the patent office identified the former patent during the search.

A backward citation is the term used for a traditional citation, and refers to the document cited in a more recent publication. A forward citation is commonly used in patent analytics and refers to the citing documents. The number of forward citations refer to citations received by a particular patent by subsequent patents. The frequency may be an indicator of key inventions or patents with high value. Publications with higher numbers of recent backward citations on the other hand are more likely to be key strategic or defensive patents.[73]

FORWARD CITATION ANALYSIS

The table below summarises the top 10 patent publications with the highest number of forward citations. The DWPI summary for the novelty described in the patent abstract is included for each publication. The more recent the application date, the more likely it is that the given publication is a key invention in the field.

There a number of patents in the dataset relating to image analysis, data analysis from electrostimulative techniques or motion detection, with intended applications of predicting/understanding physiological responses, diagnosing medical conditions or informing surgical procedures.

Some patents are assigned to large organisations identified as key in the healthcare sector throughout this report (**Philips**, **Medtronic** (including **Given Imaging Ltd**)), some to smaller companies with no clear interest in AI for healthcare (**Smart Monitor Corp**, **Aison Co. Ltd**), and one to **American Vehicular Sciences**, a subsidiary of **Acacia Research** – a well-known non-practicing entity. There were no patents pertaining to drug discovery applications or agriculture.

	No. of citations	Publication Number	Assignee - DWPI	Application Date	Publication Date
1	48	US20090318761A1	GIVEN IMAGING LTD	12/02/2009	24/12/2009
	Title: SYSTEM AND METHOD FOR IN VIVO IMAGING				

[73] Abrams et al. (2013). *Patent Value and Citations: Creative Destruction or Strategic Disruption?* National Bureau of Economic Research; NBER Working Paper No. 19647

	No. of citations	Publication Number	Assignee - DWPI	Application Date	Publication Date
	Abstract - DWPI Novelty: The system has in vivo imaging device for capturing in vivo image by illuminating light rays towards body lumen. A receiver arranged in specific distance from imaging device receives in vivo image transmitted from imaging device. A processor analyzes image data to perform processing based on automatic scene detection method. A magnetic field generator has automatic detection magnets which are controlled manually, for controlling movement of imaging device based on processed image data. A workstation has a monitor for storing and displaying stream of images.				
2	45	US20090062680A1	BRAIN TRAIN	27/08/2008	05/03/2009
	Title: ARTIFACT DETECTION AND CORRECTION SYSTEM FOR ELECTROENCEPHALOGRAPH NEUROFEEDBACK TRAINING METHODOLOGY				
	Abstract - DWPI Novelty: The method involves collecting each of multiple individual signals from multiple specified electroencephalography frequency bandwidths. A signal as a data sample is passed to an artifact detection system. A determination is made whether artifact is present in the data sample. A known value that does not reflect the artifact is substituted for the data containing the artifact if the presence of artifact is detected. The data sample is forwarded to a signal corrector that calculates root mean square amplitude. A raw amplitude graph and a corrected amplitude graph are displayed.				
3	39	US20100240988A1	REAL TIME COMPANIES	19/03/2009	23/09/2010
	Title: Computer-aided system for 360 degree heads up display of safety/mission critical data				
	Abstract - DWPI Novelty: The method involves providing non-invasive patient data derived from technology selected from MRI, X-ray, CAT scan, and sonogram. Commercial off-the-shelf (COTS) lightweight projection glasses are provided. The patient data is transformed into images. The images are transformed into three-dimensional orthogonal space on the COTS lightweight projection glasses. A surgical probe is provided with imaging capabilities. The surgical probe is inserted into a patient. The patient data is collected with the imaging capabilities.				
4	36	US20140276090A1	AMERICAN VEHCULAR SCIENCES LLC	12/05/2014	18/09/2014
	Title: DRIVER HEALTH AND FATIGUE MONITORING SYSTEM AND METHOD USING OPTICS				
	Abstract - DWPI Novelty: The method involves obtaining images of an illuminated driver by using an image obtaining device. The images are analyzed to derive measure of blood flow in a blood vessel, a capillary and a vein in a face of an occupant. The blood flow is analyzed over time to determine whether the driver loses an ability to continue to control a vehicle, where the loss of ability to continue to control the vehicle arises from the driver becoming drowsy, falling asleep or incapable of controlling the vehicle after the driver is initially awaken or controls the vehicle.				
5	34	US20080319281A1	KONINKLIJLE PHILIPS ELECTRONICS N.V.	20/06/2008	21/12/2008
	Title: Device for Detecting and Warning of Medical Condition				
	Abstract - DWPI Novelty: An electroencephalograph (EEG) unit correlates the heart beat and motion information with the brain activity to determine the presence of epileptic seizure. A processor processes and compares the signals from the EEG unit to a criterion that characterizes the epileptic seizures. An alarm unit generates an alarm upon detection of the seizure. An input/output facility reprograms the device with criteria for detecting the seizures. The facility also allows the insertion of a memory medium to provide new data or software.				
6	34	US20110230790A1	Kozlov Valeriy, Lviv, UA	27/03/2010	22/09/2011

	No. of citations	Publication Number	Assignee - DWPI	Application Date	Publication Date
	Title: Method and system for sleep monitoring, regulation and planning				
	Abstract - DWPI Novelty: The method involves entering global individual factors and daily user factors. A wake-up time interval with beginning time, end time and sleep start time is accepted from user (106). The factors and user movement data are analyzed. The intersection time between user rapid eye movement (REM) sleep phase interval and wake-up time interval is determined. The wake-up time is set within intersection time when intersection time is exists. The wake-up time is set at end time of wake-up time interval when intersection time is not exists. The user stimulated signal is created at wake-up time..				
7	32	US8046052B2	MEDTRONIC NAVIGATION INC	24/03/2010	25/10/2011
	Title: Navigation system for cardiac therapies				
	Abstract - DWPI Novelty: The system (10) has an anatomical gating device to sense a physiological event, and an imaging device (12) to capture image data of a region of patient (14) in response to the physiological event. A tracking device tracks the position of instrument in the region. A controller (28) registers the captured image data and superimposes an icon representing the instrument onto the image data of the region based upon the position tracked by the tracking device. A display (36) displays the image data with the superimposed icon of instrument.				
8	30	US20120083669A1	Abujbara Nabil M., Irvine, CA, US	04/10/2011	05/04/2012
	Title: Personal Nutrition and Wellness Advisor				
	Abstract - DWPI Novelty: The method involves receiving personal attributes and health information data for specific users (130, 140). The initial recommended daily energy and nutrients budget is estimated based on personal attributes and health information data. The ranked food item list is presented to user. The user is advised to make food item selection adjustment. The remaining daily energy and nutrient balances is adjusted based on consumed food item. The recommended food item list, rank, recommended daily energy and nutrient budget are updated in response to health-related user actions.				
9	26	US8075499B2	SMART MONITOR CORP	19/05/2008	13/12/2011
	Title: Abnormal motion detector and monitor				
	Abstract - DWPI Novelty: The method involves collecting data related to motion associated with a person or patient (108), and analyzing the collected data to determine different values characterizing the motion. Determination is made whether the seizure occurs, by comparing the values characterizing the motion to values characterizing the motion of the seizure. An alert is activated, if the seizure is determined to occur. The data is stored in long term memory for later analysis.				
10	24	US20080203144A1	AISON CO. LTD	27/12/2007	28/08/2008
	Title: Artificial Intelligence Shoe Mounting a Controller and Method for Measuring Quantity of Motion				
	Abstract - DWPI Novelty: The artificial intelligence shoe (1) has a sensor that generates ON and OFF signal, when the shoe is landed on ground and lifted from the ground to measure the walking speed of the user. A measurement unit comprises contact electrodes for supplying current into the body of the user to measure the body fat. A controller comprises a display unit (3) for displaying calorie consumption of the user, which is calculated based on the walking speed and body fat of the user measured using the sensor and measurement unit.				

BACKWARD CITATION ANALYSIS

The table given below summarises the top 10 patent publications with the highest number of backward citations. As with the forward citation analysis, the DWPI Novelty has been included for each publication.

The subjects of the patents in the dataset are based mostly on patient monitoring and medical device navigation/positioning. Large key players are again represented, with **Medtronic**, **Abbott Laboratories** and **Philips** (through subsidiary **Volcano Corp**) assigned patents for cardiac therapy navigation, data management in analyte monitoring, and image calibration, respectively. Several other specialised companies focusing on medical devices (**CR Bard**), motion recognition (**Medibiotics**) and patient monitoring systems (**Dexcom**, **Alivecor**, **Masimo**) also hold important patents. One filing from **Elwha LLC** is also featured, titled *Unmanned device interaction methods and systems*. **Elwha LLC** is a holding company of **Intellectual Ventures**, itself a patent holding company.

<table>
<tr><th></th><th>No. of citations</th><th>Publication Number</th><th>Assignee - DWPI</th><th>Application Date</th><th>Publication Date</th></tr>
<tr><td rowspan="3">1</td><td>905</td><td>US8971994B2</td><td>BARD INC C R</td><td>08/04/2013</td><td>03/03/2015</td></tr>
<tr><td colspan="5">Title: Systems and methods for positioning a catheter</td></tr>
<tr><td colspan="5">Abstract - DWPI Novelty: The position depicting method involves inserting a stylet (92), which includes a permanent magnet, into a blood vessel. A detector is then positioned such that its first detection zone includes a portion of the vessel. Measurements of the magnetic field generated by the magnet are then obtained via the detector, then determining first and second confidence levels regarding the first and second positions of the magnet. A representative image of the magnet is then displayed if the second position is within the first and second detection zones and the confidence level is above a threshold value.</td></tr>
<tr><td rowspan="3">2</td><td>868</td><td>US20140270445A1</td><td>VOLCANO CORP</td><td>12/03/2014</td><td>18/09/2014</td></tr>
<tr><td colspan="5">Title: SYSTEM AND METHOD FOR OCT DEPTH CALIBRATION</td></tr>
<tr><td colspan="5">Abstract - DWPI Novelty: The method involves obtaining an image that includes a target and a reference item. A location of the reference item is detected within the image. A y-value of the location is determined. The determined y-value is compared to a stored reference y-value. A calibration value based on the comparison is calculated. A calibrated image is provided by shifting pixels in a y-direction according to the calibration value. A reference item comprises an image of a sheath of a catheter (826). The pixels are shifted by the difference by removing a feature from the image.</td></tr>
<tr><td rowspan="2">3</td><td>621</td><td>US9795301B2</td><td>NATIONAL INSTITUTES OF HEALTH (NIH) U.S. DEPT. OF HEALTH AND HUMAN SERVICES (DHHS) U.S. GOVERNMENT</td><td>25/05/2011</td><td>24/10/2017</td></tr>
<tr><td colspan="5">Title: Apparatus, systems, methods and computer-accessible medium for spectral analysis of optical coherence tomography images</td></tr>
</table>

	No. of citations	Publication Number	Assignee - DWPI	Application Date	Publication Date
	Abstract - DWPI Novelty: An information generating apparatus (200) comprises at least one first arrangement which is configured to receive at least one first radiation from the structure and at least one second radiation from a reference, and interfere the first and second radiations to generate at least one third radiation; and at least one second arrangement which is configured to generate spectroscopic data as a function of the third radiation, and reduce at least one scattering effect in the spectroscopic data to generate the information.				
4	601	US9067070B2	MEDIBOTICS LLC; CONNOR ROBERT A	12/03/2013	30/06/2015
	Title: Dysgeusia-inducing neurostimulation for modifying consumption of a selected nutrient type				
	Abstract - DWPI Novelty: The method involves detecting consumption of a selected nutrient type by a person by analyzing a chemical composition of food, saliva and/or chyme in person's oral cavity, esophagus, stomach and/or duodenum. Temporary dysgeusia is induced in response to the consumption of the selected nutrient type, where the dysgeusia is induced by the application of electromagnetic energy to an afferent member of person's peripheral nervous system, where the afferent member conveys signals for a portion of the way from person's taste receptors to person's brain, and the dysgeusia modifies the consumption.				
5	528	US9798325B2	ELWHA LLC	31/08/2012	24/10/2017
	Title: Unmanned device interaction methods and systems				
	Abstract - DWPI Novelty: The system has a circuitry obtaining an indication of a first time interval from when a device-detectable energy signature path exists between first and second entities i.e. unmanned aerial devices (UADs) (201, 202) until a reference time. A circuitry signals a decision whether or not to change an aerial navigation protocol of the first entity as an automatic and conditional response to a result of comparing the threshold against the indication of the first time interval from when the energy signature path exists between the first and second entities until the reference time.				
6	495	US8046052B2	MEDTRONIC NAVIGATION INC	24/03/2010	25/10/2011
	Title: Navigation system for cardiac therapies				
	Abstract - DWPI Novelty: The system (10) has an anatomical gating device to sense a physiological event, and an imaging device (12) to capture image data of a region of patient (14) in response to the physiological event. A tracking device tracks the position of instrument in the region. A controller (28) registers the captured image data and superimposes an icon representing the instrument onto the image data of the region based upon the position tracked by the tracking device. A display (36) displays the image data with the superimposed icon of instrument.				
7	421	US9282925B2	DEXCOM INC	25/03/2010	15/03/2016
	Title: Systems and methods for replacing signal artifacts in a glucose sensor data stream				
	Abstract - DWPI Novelty: The method involves receiving data from a continuous analyte sensor (10) i.e. continuous glucose sensor. An occurrence of a signal artifact event is detected by determining amplitude of sensor data and determining amplitude of a signal artifact or by detecting start of the signal artifact event when the amplitude of the signal artifact meets a predetermined condition. The received data is processed according to presence or absence of the signal artifact event. The received data is filtered to generate filtered data.				

	No. of citations	Publication Number	Assignee - DWPI	Application Date	Publication Date
8	392	US9579062B2	ALIVECOR INC	20/11/2015	28/02/2017
	Title: Methods and systems for electrode placement				
	Abstract - DWPI Novelty: A device has a non-transitory computer readable storage medium encoded with a computer program including instructions executable by processor to cause processor to compare normalized picture of patient to electrode placement database and determine positions of electrodes on patient from comparing, and present image of the patient showing determined positions of electrodes on image of patient. The electrode placement database has representations of body types and predetermined electrode placement positions corresponding to each body type.				
9	367	US9697332B2	ABBOTT DIABETES CARE INC	08/12/2014	04/07/2017
	Title: Method and system for providing data management in integrated analyte monitoring and infusion system				
	Abstract - DWPI Novelty: The apparatus has a memory operatively coupled to one or more processors for storing instructions. The processors associate a meal event with a rate of change of monitored analyte level when the rate of change exceeds a preset threshold level. The processors determine an optimal medication administration profile based on the rates of change of the monitored analyte level and the automated pattern recognition when number of the rates of change of the monitored analyte level over the preset time period associated with the meal event exceeds the preset number.				
10	231	US9636056B2	MASIMO CORP	10/04/2015	02/05/2017
	Title: Physiological trend monitor				
	Abstract - DWPI Novelty: The monitor has an alarm indicator that receives smoothed measurement values (412) of physiological parameter and predictive values of physiological parameter, an alarm, and a memory that stores first and second criteria and each indicative of alarm conditions (305). First criteria are relevant to smoothed values and second criteria are relevant to predictive values. Alarm indicator compares features to first and second criteria, and triggers alarm when a feature matches first and second criteria respectively.				

COMMENTARY ON GRANTING OF PATENTS

There are a number of commentators who have highlighted the issue of patent eligibility for inventions in AI, framed in the broader context of software patents since AI involves, at its core, computer-implemented algorithms. Patenting software-related inventions has been at the centre of the patent-eligible subject matter debate for a long time now. While getting a grant of a software patent in India, for instance, has often been difficult, the US has traditionally been a more pro-software patent jurisdiction, while the European Patent Office is somewhere in the middle of the two.[74]

However, some well-known cases of legal decisions in software patent cases deeming software to be ineligible patent subject matter due to abstractness of the idea, such as the US Supreme Court 2014 decision in **Alice Corp** *v.* **CLS Bank**, have subsequently hindered patents for computer-related inventions, particularly software patents.[75] But more recent US

[74] https://sigtuple.com/blog/protecting-ai-inventions/

[75] https://www.lexology.com/library/detail.aspx?g=300e6862-012d-49dd-bed4-ba8ae4477397

decisions have clarified the stance on the issue, and cases like **Enfish** ***v*****. Microsoft** have categorically stated that software claims are patent eligible subject matter.

In general, a mathematical algorithm *per se* is not patentable but may be so if implemented on a computer in a manner that produces some useful, material outcome such as an improvement in the functioning of the computer or some other useful result. The approach taken is that for a software or algorithm invention the software or algorithm itself does not render an invention patentable. For an invention to be eligible for a patent there must be something more than mere generic computer implementation.[76]

The question of patent eligibility is important for companies, organisations and researchers innovating in the fields of big data analytics, cloud computing services, machine learning, etc. and for which software needs to be patent-eligible subject matter. However, some commentators have pointed out the drawbacks of issuing patents in the AI space. For example, **Google** has a patent on a common machine learning technique called Dropout. This means that **Google** could insist that no one else use this technique until 2032, but patents on such fundamental machine learning techniques have the potential to fragment development and hold up advances in AI.[77] It is also been argued that some patents have been issued for using machine learning techniques in obvious and expected ways.[78]

We are moving rapidly towards a future where artificial intelligence will play a hugely significant part, and innovations in the field need to be adequately protected. Though it is true that granting frivolous patents empowers patent trolls and costs companies millions to fight subsequent lawsuits, at the same time, an anti-software patent approach is equally bad in terms of not being able to protect true technological breakthroughs and inventions in areas which are likely to shape the future of many technology areas.[74]

In addition to patent eligibility common to software products, there are some unique features of AI systems which give rise to new IP challenges. One of these is the need to train the system using large volumes of data. Training is often crucial, as it allows the system to develop and refine its decision making abilities to the point where they start to become comparable with human decision making, putting the “intelligence” into AI.[79] How this need to train the system impacts on the IP issues will depend on the parties involved in the development, and the way an AI system is trained will influence who owns the IP in the finished product.

This can become complicated where there are multiple parties involved in its development. If one party supplies the initial code but a second trains it, there is the potential for conflict as to who owns the IP rights in the resulting system. Unlike a traditional software development situation where every line of code is attributable to a human author, using machine learning will generate large sections of code automatically. The approach the

[76] https://gestalt.law/artificial-intelligence-patents-for-healthcare/

[77] http://www.i-programmer.info/news/105-artificial-intelligence/8765-google-files-ai-patents.html

[78] https://www.eff.org/deeplinks/2017/09/stupid-patent-month-will-patents-slow-artificial-intelligence

[79] http://digitalbusiness.law/2017/06/artificial-intelligence-and-ip-part-1-developing-ai-systems/

parties take to IP ownership issues in their commercial agreements will need to adapt to reflect this process.[79]

Another issue with IP in AI systems has the potential to be even more disruptive; creating content using AI. AI systems are not considered legal persons and there is no single law which sets out who will own the IP rights in any content they create. The position for the near future will therefore depend on how our existing framework for ownership of each type of IP right can be made to fit situations where an AI system is involved in creating the relevant content.[80] On a practical level, the best way to manage the potential uncertainties regarding ownership of IP rights in content generated by an AI system will be to clearly set out who is going to own the IP in commercial agreements and terms of use for the system. Given the number of entities which could be involved in the design, training and use of an AI system, these issues will need to be thought through right at the outset of an AI project and applied at each contacting stage as the project develops.[80]

One further issue for securing patent protection for AI-based inventions is satisfying disclosure requirements. An inventor must disclose to the public enough information about the invention to enable one of ordinary skill in the art to practice what is claimed. Given the nature of some AI inventions, meeting this requirement can be challenging. For example, when seeking protection for rule-based AI systems, a research team may have developed rule sets that are effective for a specific application. Patent claims directed to a broader scope of application may not be enabled by the rules developed. Disclosing only those specific rules may not satisfy the disclosure obligations. The performance of AI embodied in artificial neural networks can depend on network topology, which can include the number and types of layers, the number of neurons per layer, neuron properties, training algorithms and training data sets. The scope of the claims will depend on what the limited set of topologies disclosed in the patent teaches one skilled in the art to practice. There could be millions of permutations of the network architecture or rules adaptable for various applications. Disclosing only a few and trying to define a broad claim scope may introduce risks.[81]

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[80] http://digitalbusiness.law/2017/06/artificial-intelligence-and-ip-part-2-ip-in-ai-generated-content/

[81] https://www.finnegan.com/en/insights/intellectual-property-protection-for-artificial-intelligence.html

APPENDIX

DEALS

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
Insilico Medicine	Drug discovery	MD, USA	GSK	Partnership	2017	4	8.26
WuXiNextCode	Drug discovery	MA, USA	Amgen Ventures, 3W Partners	Venture	2017	165	255
Tempus Labs	Diagnostics	Chicago, USA	New Enterprise Associates, Lightbank	Venture	2017	70	70
Exscientia	Drug discovery	Dundee, Scotland	GSK, Sanofi	Research collaboration	2017	42.7	42.7
Infervision	Diagnostics	Beijing, China	Genesis Capital (China)	Venture	2017	18.2	25.45
Wellframe	Virtual nursing	MA, USA	Draper Fischer jurvetson, Carl Byers	Venture	2017	15	25.3
VoxelCloud	Imaging	CA, USA	New Margin Ventures, Sequoia	Venture	2017	15	28.5
bioAge Labs	Drug discovery	Salt Lake City, Utah	Sanofi		2016		
twoAR	Drug discovery	Palo Alto, California	Santen Pharmaceuticals		2017		
Deep Genomics	Drug discovery		Khosla Ventures, Bloomberg Beta, True Ventures	Venture	2017	13	16.74
AiCure	Patient Monitoring	NY, USA	New Leaf Venture Partners	Venture	2017	11.94	27.68
BioAge Labs	Drug discovery	USA		Venture	2017	10.9	10.9
Teckro	Clinical trials	Ireland		Venture	2017	10	16
Qrativ	Drug Discovery	MA, USA		Venture	2017	8.3	8.3
Bright.MD	Virtual nursing			Venture	2017	8	12.57
Freenome	Diagnostics		Data Collective, CRV, Andreessen	Venture	2017	7	79.05

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
			Horowitz				
Buoy Health	Virtual nursing			Venture	2017	6.7	9.22
Cardinal Analytx	Personalised medicine			Venture	2017	6.1	8.88
Sensome	Patient Moitoring	France		Venture	2017	5.4	5.4
Cogitativo	Hospital workflow	CA, USA	HSC Ventures	Venture	2017	5	5
CloudMedX	Hospital workflow	CA, USA		Venture	2017	4.23	10.95
Binary Fountain	Hospital workflow	USA		Venture	2017	4	25.7
Siris Medical				Venture	2017	4	4
Athleas	Diagnostics	CA, USA	Elad Gil, Initialized Bapital, GPU Technologies	Seed	2017	4.08	
Imsight Medical	Medical Imaging	China	Lenovo Ventures Group	Venture	2017	2.95	
Signature Medical	Diagnostics	Boston, USA	Allied Minds, Bose Ventures	Venture	2017	2.5	
Health Rythms							
iCarbonX	Diagnostics		Tencent Holdings, Vcanbio	Venture	2016	154	
Flatiron	Hospital workflow	New York, USA	Casdin Capital, Baillie Gifford, BoxGroup, Aaron Levie	Venture	2016	175	313
Desktop Genetics	Personalised medicine	UK		Venture	2016	0.4	2.2
Robin	Software	CA, USA	First Round Capital, Marc Benioff	Venture	2017	undisclosed	undisclosed
Precision Health AI	Internet	New York	Symphony Technology Group	Series A	2017	20	20
Sophie Bot	Mobile & Telecommunications	Nairobi	Merck Accelerator;Nailab	Incubator/Accelerator	2017	0.01	0.01
NarrativeDx	Internet	Austin	Capital Factory;Cultivation Capital;DreamIt Ventures;Floodgate;HealthX Ventures;Live Oak Ventures;LiveOak Venture	Seed - II	2017	0.12	5.59

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
			Partners;Silverton Partners;Techstars;Undisclosed Investors				
GYANT	Mobile & Telecommunications	San Francisco	Plug and Play Accelerator;Techstars	Seed	2017	0.12	0.12
Resurgo Genetics	Healthcare	London	Entrepreneur First	Pre-Seed	2017	0.01	0.01
doc.ai	Mobile & Telecommunications	Palo Alto	Undisclosed	Convertible Note	2017	2.28	2.28
Sensum Technologies	Software (non-internet/mobile)	London	Entrepreneur First	Pre-Seed	2017	0.01	0.01
GTN	Healthcare	London	Entrepreneur First	Pre-Seed	2017	0.01	0.01
Machine Medicine	Consumer Electronics	London	Entrepreneur First	Pre-Seed	2017	0.01	0.01
Oncora Medical	Software	DE, USA	BioAdvance, Dorm Room Fund	Seed - III	2017	1.89	3.21
MyndYou	Mobile Software	Israel	Howard Morgan, Musketeer Capital	Seed VC	2017		1.2
DeepWise	Software	Beijing, China	Undisclosed	Seed	2017	5.36	27.94
babylon	Mobile & Telecommunications	London	Digital Health London	Incubator/Accelerator	2017	undisclosed	85
WellSheet	Internet Software	NY, USA	Undisclosed	Venture	2017	0.57	0.67
Reverie Labs	Drug Development	MA, USA	Rough Draft Ventures	Seed VC	2017	0.03	0.03
WellTok	Software	CO, USA	BIRD Foundation	Grant	2017	undisclosed	311.64
GenomeDx Biosciences	Diagnostics	BC, Canada	Aeris Capital, Baird Venture Partners	Series C	2017	6.25	11.16
Cofactor Genomics	Diagnostics	MO, USA	Menlo Ventures, Ascension Ventures, Data Collective	Series A	2017	18	19.62
Your.MD	Mobile & Telecommunications	London	Orkla Venture Fund, Smedvig Capital	Series A	2017	10	15
Pine Biotech	Software	LA, USA	Undisclosed	Angel	2017	1.03	1.03

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
GeneLife	Software	Beijing, China	Huiding Capital	Series A	2017	7.4	7.4
SharkDreams	Software	NC, USA	Undisclosed	Venture	2017	0.85	1.85
Cardinal Analytx	Software	CA, USA	Undisclosed	Venture	2017	2.78	8.88
Whole Biome	Drug Development	CA, USA	True Ventures	Series A	2017	10.5	10.5
Multiplier Solutions	Software	Hyderabad, India	Norwest Venture Partners	Seed VC	2017	1.5	1.5
VitaDX	Software	Rennes, France	Auriga, Go Capital	Seed VC	2017	1.8	3.5
physIQ	Medical devices	IL, USA	4490 Ventures, GF Securities	Series B	2017	8	19.91
MedWhat	Mobile & Telecommunications	FL, USA	Undisclosed	Venture	2017	2.64	3.76
Aidence	Diagnostics	Netherlands	Haaglanden Hospital Group	Seed	2017	2.52	2.52
Deep Radiology Corp	Software	CA, USA	Undisclosed	Seed	2017	1	1
VoxelCloud	Software	CA, USA	Sequoia Capital China	Series A	2017	8	28.5
SigTuple	Software	India	Launchpad Accelerator	Incubator/Accelerator	2017	5.8	5.8
Day Zero Diagnostics	Medical devices	MA, USA	Golden Seeds & undisclosed investors	Seed	2017	2	3.01
RX Health	Mobile & Telecommunications	India	DesignGild	Seed	2017	undisclosed	
HealthReveal	Software	NY, USA	Northwell Ventures	Series A	2017	0.5	11.3
My Intelligent Machines	Software	Canada	FounderFuel	Seed	2017	0.08	0.08
Proscia	Software	MD, USA	Undisclosed	Venture	2017	0.93	2.03
GNS Healthcare	Software	MA, USA	Celgene, Alexandria Real Estate Equities, Gi Global Health Fund LP	Series C	2015	10	
MIT	Healthcare	MA, USA	IBM Watson	Research collaboration	2017	240	
UCSF	Healthcare	CA, USA	GE Healthcare	Research collaboration	2016		

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
CareSkore		IL, USA	Storm ventures, Cota Capital, Rising Tide Fund, Liquid 2 Ventures	Seed	2016	4.3	
Zephyr Health		CA, USA	Kleiner Perkins Caufield & Byers and Jafco Venture	Series B	2014	15	
Sentrian		CA, USA	TELUS Ventures, Reed Elsevier Ventures and Frost Data Capital	Seed	2014	12	
Butterfly Network		MA, USA	undisclosed	Venture	2014	80	100
3Scan	Drug Discovery	CA, USA	Lux Capital, Data Collective, Dolby Family Ventures, OS Fund, Comet Labs and Breakout Ventures	Series B	2016	14	22
Enlitic	Imaging	Ausralia	Capitol Health Limited	Partnership	2015	10	
Arterys	Diagnostics	CA, USA	GE Ventures, Stanford-StartX Fund	Series A	2016	12	
Atomwise	Drug Discovery	MA, USA	Data Collective, Khosla Ventures, DFJ, AME Cloud Ventures and OS Fund	Seed	2015	6	
Recursion Pharmaceuticals	Drug Discovery	UT, USA	Data Collective, Lux Capital, Obvious Ventures, Advantage Capital, Felicis, Epic, AME, Mubadala, Menlo Ventures, CRV, Two Sigma and High-Value Angel Investors	Series B	2017	60	80
MIT	Healthcare	USA	IBM Watson	Partnership			
Truven Health Analytics		NY, USA	IBM Watson	Acquisition	2016	2.6 billion	
Explorys		NY, USA	IBM Watson	Acquisition	2015	undisclosed	
Phytel		NY, USA	IBM Watson	Acquisition	2016	undisclosed	
Partners		MA, USA	GE	Partnership	2017		

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
HealthCare							
McCoy Medical Technologies		PA, USA	TeraRecon	Acquisition	2017	undisclosed	
Mendel Health		CA, USA	Cancer Genetics, Inc	Partnership	2017		
Lantern Pharma		CA, USA	Cancer Genetics, Inc	Partnership	2017		
Arsenal Health		MA, USA	athenahealth	Acquisition	2016	undisclosed	
Alpine Data		CA, USA	TIBCO Software	Acquisition	2017	undisclosed	
Arm		TX, USA	Nano Global	Licensing agreement	2017	undisclosed	
WPC Healthcare		TN, USA	Intermedix	Acquisition	2017	undisclosed	
Meta		USA	Chan Zuckerberg Inititative	Acquisition	2017	undisclosed	
Alexion	drug discovery	MA, USA	GNS Healthcare	Licensing agreement	2017		
Sanford Health		IL, USA	Tempus	Partnership	2017		
University of California		IL, USA	Tempus	Partnership	2017		
Rush University Medical Center		IL, USA	Tempus	Partnership	2017		
DiA Imaging Analysis		Israel	GE Healthcare	Licensing agreement	2017	undisclosed	
IBM Watson	Drug discovery	USA	Pfizer	Partnership	2016		
Numerate	Drug discovery	San Bruno, California	Takeda Pharmaceuticals	Partnership	2017		17.4
GNS Healthcare	Drug discovery	Cambridge, Massachusetts	Genentech (Roche)	Partnership	2017	6	35.75
Benevolent AI	Drug discovery	London, UK	Janssen	Partnership	2016		
Atomwise	Drug discovery	US	Merck	Partnership	2015		
Berg	Drug discovery	MA, USA	Sanofi, AstraZeneca	Partnership	2017		
Marvx Imaging	Internet	USA	Entrepreneur First	Pre-seed	2013	-	12.40
Benson Hill	Internet	USA	Undisclosed Investors		2013	0.30	34.21

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
Biosystems							
Spensa Technologies	Agriculture	USA	Emerging Innovations Fund		2013	0.02	2.65
Benson Hill Biosystems	Internet	USA	Undisclosed Investors		2013	0.25	34.21
Spensa Technologies	Agriculture	USA	Village Capital	Seed	2013	0.05	2.65
Benson Hill Biosystems	Internet	USA	BioGenerator	Seed	2013	0.40	34.21
Benson Hill Biosystems	Internet	USA	BioGenerator	Seed	2013	0.13	34.21
Climate Corporation	Agriculture	USA	Monsanto	Acquisition	2013	930	-
GeoVisual Analytics	Internet	USA	NASA	Grant	2014	0.12	1.69
Benson Hill Biosystems	Internet	USA	BioGenerator	Seed	2014	0.03	34.21
Slantrange	Agriculture	USA	The Investor Group; Motus Ventures	Series-A	2016	5	-
Gamaya	Agriculture	Switzerland	Chairman and former CEO of Nestle, Peter Brabeck-Letmathe; the Sandoz Foundation; Swiss venture capital firm VI Partners	Venture	2016	3.2	-
Second Genome	Agriculture	USA	Monsanto Co.	Research Collaboration	2016	-	-
Microsoft Corporation India Private Ltd	Agriculture	India	Government of Karnataka	Research Collaboration	2017	-	-
Atomwise	Agriculture	USA	Monsanto Co.	Research Collaboration	2017	-	-
Blue River Technology	Agriculture	USA	Deere & Company	Acquisition	2017	305	-

Company	Sector	Location	Acquirer/investor/licencee	Deal type	Year	Deal Financial $m	Total Financial $m
Slantrange	Agriculture	USA	Bayer Crop Science	Research Collaboration	2017	-	-
Ceres Imaging	Agriculture	USA	Romulus Capital	Venture	2017	2.5	10.5
Ceres Imaging	Agriculture	USA	Romulus Capital	Venture	2017	5	10.5
Abundant Robotics	Agriculture	USA	GV; BayWa AG; Tellus Partners; Yamaha Motor Company; KPCB Edge; Comet Labs	Venture	2017	10	-
Uptake	Agriculture	USA	Baillie Gifford; GreatPoint Ventures; Revolution Growth	Venture	2017	117	264
Tortuga AgTech	Agriculture	USA	Root Ventures; Susa Ventures; Haystack; AME Cloud Ventures; Grit Labs; Stanford-StartX Fund; SVG Partners	Seed	2017	2.4	-
Orbital Insight	Geospatial analytics/ Satellite Imagery	USA	Sequoia; Envision Ventures; Balyasny Asset Management; Geodesic Capital; ITOCHU Corporation; Intellectus Partners	Series C	2017	50	78.7