Signify Research

WHITE PAPER

What's new for machine learning in medical imaging

Predictions for 2019 and beyond

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Introduction

It is becoming increasingly clear that machine learning will transform many aspects of healthcare delivery, with imaging-enabled specialties such as radiology and pathology set to be early adopters. In the coming years, medical imaging professionals will have a rapidly expanding AI-enabled diagnostic toolkit at their disposal, to support with all aspects of image interpretation from detection, classification and segmentation, through to the extraction of quantitative imaging features and biomarkers. In addition to supporting the diagnostic process and improving clinical outcomes, machine learning will also boost productivity from the use of smart workflow and reporting tools. There are also applications for machine learning beyond image interpretation, from helping imaging departments to maximise their operational performance, to tools that enhance the image acquisition process, ensuring the best quality image is obtained for each examination.

With the medical imaging industry at the start of a new wave of AI-fuelled technology innovation, and one that is set to disrupt all aspects of the profession, now is the time for health providers to establish an AI roadmap to ensure they fully benefit and remain competitive. The aim of this white paper is to highlight some of the trends that will impact the market in the coming years and to provide insights into the underlying technologies that are reshaping the future of medical imaging.

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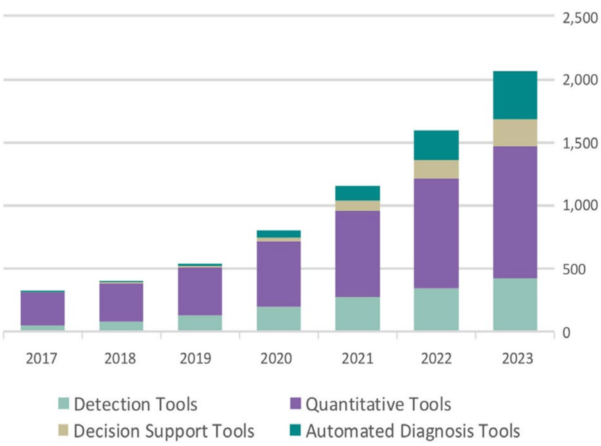
Prediction 1

The market for machine learning in diagnostic imaging will top $2 billion by 2023.

The use of machine learning technology in diagnostic imaging is by no means new and can be traced back to the late 1990s when the first solutions to detect breast cancer in mammograms entered the market. However, these early solutions used manually crafted algorithms that required extensive clinical domain expertise and they largely failed to live-up to expectations due to the high rate of false positives when compared with human readers. Consequently, the use of machine learning in routine diagnostic imaging has to date been limited. That is poised to change dramatically in the coming years following the introduction of deep learning techniques, such as convolutional neural networks. Through feature learning instead of feature engineering, whereby systems automatically learn the representations needed for feature detection or classification from labelled training data, deep neural networks promise faster and more accurate results. Coupled with advancements in IT infrastructure and the availability of affordable GPU compute and high performance data storage, the pace of product development for AI-based medical image analysis is faster than ever before.

Figure 1 World market for AI-based medical image analysis software - revenue forecast ($m)*



Source: Signify Research

** Quantitative tools category includes both ML and non-ML solutions*

Figure 2 Market drivers and barriers for AI-based medical image analysis software

MARKET DRIVERS

- Increasing radiologist workload
- Errors and discrepancies in radiology practice
- Shortage of radiologists in many countries
- Growing use of quantitative imaging and imaging biomarkers in clinical practice
- The increasing use of AI beyond image analysis, for example practice management, quality assurance and image acquisition
- Risk stratification for population-based imaging initiatives
- Improved performance of deep learning algorithms over early generation AI
- Rapid pace of development in core infrastructure, e.g. storage, compute and networking
- Smart image acquisition hardware with embedded AI
- Huge R&D investment from growing ecosystem of market players, including startups, incumbent medical imaging vendors and big technology vendors

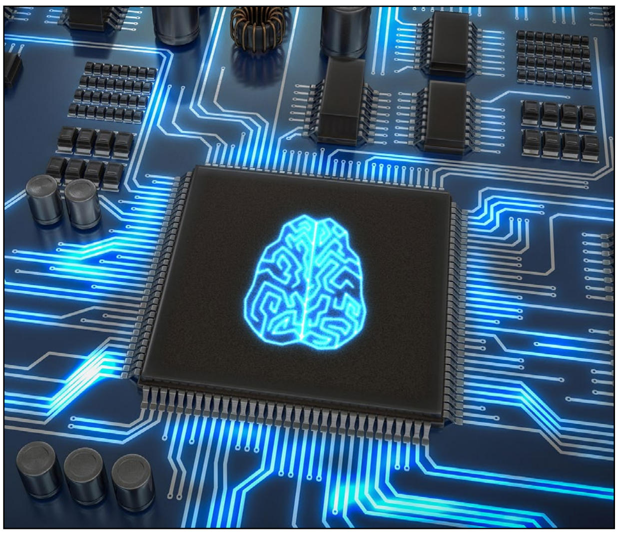
MARKET BARRIERS

- Relatively few products on the market
- The slow regulatory approval process
- Lack of large scale clinical validation of the efficacy of deep learning algorithms in the field
- Lack of reaJ-world evidence to demonstrate the economic benefits and the return on investment
- Integration in the clinical workflow
- An effective route to market for algorithm developers
- Lack of annotated data to train deep learning algorithms
- Opacity of AI results due to the black box nature of deep learning algorithms
- Long sales and implementation cycles
- Ethical and legal issues

BARRIERS STILL REMAIN

While the market holds great promise, it is still in the innovator and early adopter phase and there are several barriers that need to be overcome before AI becomes mainstream in medical imaging. The major barriers include:

1. The regulatory process remains challenging and there are few approved products on the market. The recent announcement from the US FDA that it plans to introduce a pilot software precertification program, called Digital Health Software Precertification, is expected to expedite the regulatory process to some extent
2. More large-scale validation studies are needed to show the performance of deep learning algorithms in real-world clinical settings and boost radiologist confidence in AI
3. The results from AI-based image analysis tools need to be fully integrated into radiologists' workflows and presented at the time of the primary read. Algorithm developers need to partner with imaging IT vendors to ensure their solutions are tightly integrated
4. Healthcare providers are reluctant to purchase AI tools from multiple companies due to vendor specific integration challenges and the administrative overhead. Algorithm developers need to establish effective routes to market, such as distribution deals with established medical imaging vendors and the new breed of vendor-neutral AI platforms



Prediction 2

Machine learning will improve the radiology patient experience, at every step.

Much of the initial focus for the application of machine learning in medical imaging has been on image analysis and developing tools to make radiologists more efficient and productive. The same tools will often enable more precise diagnosis and treatment planning, or help to reduce missed diagnoses, thus leading to improved patient outcomes. However, AI and machine learning have a much broader role to play in radiology beyond clinical decision making and it can help to improve the patient's experience throughout the imaging process, from the initial scheduling of the imaging examination to the end diagnosis and follow-up.

Figure 3 Use-cases for machine learning in radiology

- Asset utilization and case load management
- Predict patient no-shows
- Follow-up on incidental findings

- Automatic protocol selection and system optimization
- Faster scan times
- Lower dose

- Automatic triage
- Smart hanging protocols, image registration and image fusion
- Feature detection, segmentation and quantification
- Decision support and differential diagnosis

- Automatically populate radiology reports with quantitative results
- Quality assurance

- Biomarkers for predicting prognosis and therapeutic response
- Personalised treatment planning for individual patients
- Automatic contouring for radiation planning

- Automatically schedule post-imaging follow-up

SCHEDULING

Greater use of analytics and machine learning will help radiology departments to streamline their operational efficiency, by continuously monitoring and improving asset utilization and workflows to help achieve productivity gains. Improving operational efficiency will not only impact the bottom line, but it will also help resource-bound imaging departments to see more patients and reduce patient wait times for appointments.

Specifically, machine learning can be used to predict patient cancellations and no-shows, a major challenge for most imaging departments that results in financial loss and delays to patient care. Additionally, the combination of natural language processing (NLP) and machine learning can ensure that clinically relevant incidental findings from radiology reports are actively monitored with any follow-up exams both scheduled and completed.

IMAGE ACQUISITION

There are multiple applications for machine learning during the image acquisition process, from automatic image protocol selection, to ensuring the patient is correctly positioned during the scan. Both can lead to fewer repeat scans, saving time for both the health provider and the patient.

In the case of X-ray and CT exams, getting the scan right first time can also avoid the additional radiation dose exposure from repeat exams. Furthermore, the use of machine learning during image reconstruction can enhance the quality of low-dose CT scans to that of normal dose CT scans, further reducing patient radiation exposure.

AI-powered image analysis during an MRI exam will reduce scan times by skipping unnecessary sequences. If nothing is found from the initial sequences, the scan can be completed sooner and potentially avoid unnecessary use of contrast. Machine learning can also reduce scan times by enhancing under-sampled scans obtained from faster image acquisition speeds. Decreasing MRI scan times helps radiology departments to increase patient throughput and reduce patient waiting times, not to mention the improved patient comfort.

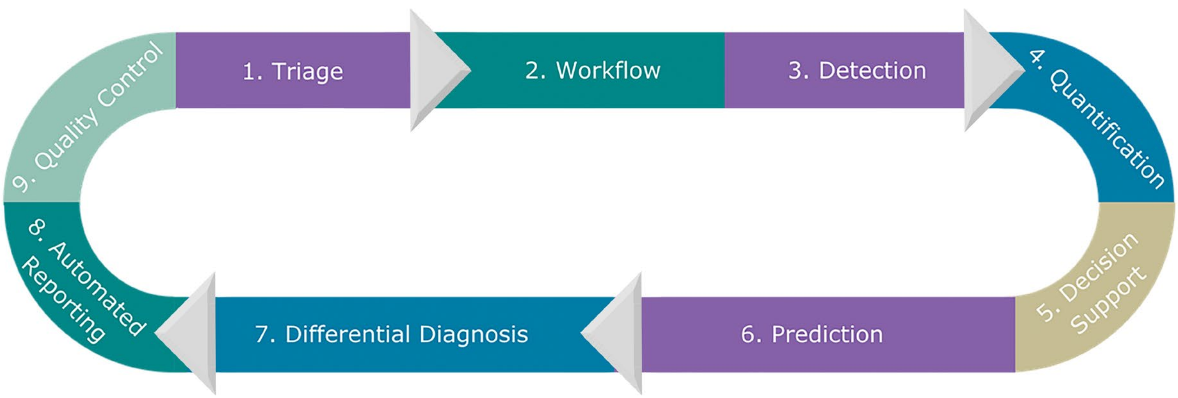
In the coming years, machine learning will also address one of the fundamental challenges with MRI exams – patient movement during scanning causes artefacts in the MR images. By comparing motion-degraded images with their respective re-scans, deep learning algorithms can learn to identify and suppress motion artefacts, both during image acquisition and post-processing. AI-based motion correction could lead to a reduction in repeat scans and potentially reduce the need for sedation in children, leading to cost savings for the radiology department and an improved patient experience

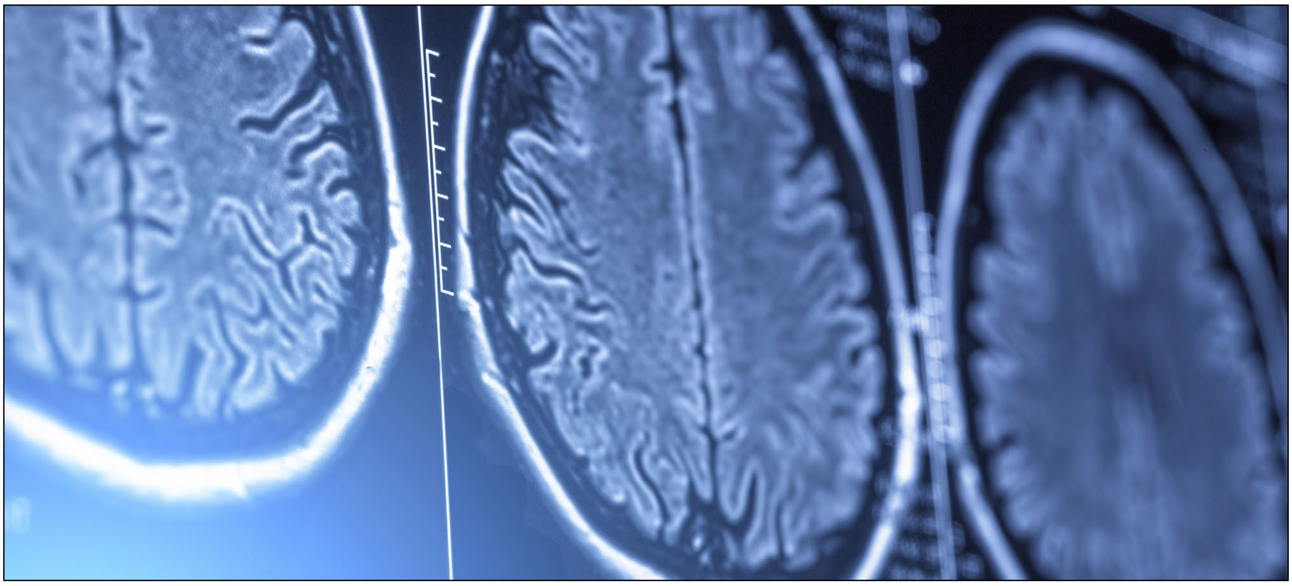
IMAGE ANALYSIS

Machine learning is set to augment every step of the image analysis process, as shown in the diagram below, in each case leading to faster and more accurate diagnoses and hence improved patient outcomes.

At the very beginning of the image analysis workflow, machine learning will be used to triage incoming studies based on the initial AI findings, to route the study to the appropriate specialist and

Figure 4 Machine learning in medical image analysis





prioritise abnormal cases in the reading list. This will enable radiologists to make faster and more accurate diagnoses, particularly for time-sensitive acute conditions, such as ischemic stroke.

Once the radiologist opens a new case, machine learning will search for any clinically relevant prior studies, automatically register studies, select the hanging protocol and provide the radiologist with contextually relevant tools and supporting information, for example from the patient's electronic medical record. In parallel, machine learning will automatically detect, segment, visualize and quantify any abnormalities. If an abnormality is detected, machine learning will then provide diagnostic decision support, such as a probability score for malignancy or a differential diagnosis.

REPORTING

Writing text-based radiology reports is a time-consuming task and prone to human error. Machine learning can pre-populate reports with quantitative results and clinical findings for the radiologist to approve or edit. Not only will machine learning make radiology reports more precise, but it will also help to ensure consistency of reporting across an organisation. Moreover, referring physicians are increasingly requesting structured radiology reports with quantitative results rather than purely text-based reports. Radiology practices who offer this are more likely to retain customers and win new ones. Once the preliminary report is prepared, AI can provide quality assurance by ensuring the clinical findings have been accurately reported and nothing has been missed.

TREATMENT PLANNING & FOLLOW-UP

Machine learning will accelerate the use of quantitative imaging in routine clinical practice by automating the time-consuming task of manually taking measurements. Clinically validated imaging biomarkers can help to improve diagnostic accuracy, to determine prognosis and to predict therapeutic response, leading to more personalised, data-driven treatment planning for individual patients.

Machine learning will also play a key role in treatment planning decision support, by leveraging past patient data to inform decision making. By searching previous treatment outcomes for patients who presented with similar disease characteristics to the current case, for example patients with lung nodules with a similar size, shape, texture and growth rate, the most effective treatment plan can be selected for each individual patient. This will lead to shorter treatment planning cycles and potentially eliminate the need for treatment planning iterations, saving costs and improving treatment outcomes.

In summary, machine learning will increasingly be applied at every step of the radiology workflow, leading to improved operational efficiency and cost savings for health providers, along with faster, more accurate and personalised diagnosis and outcomes for patients.

Prediction 3:

New and compelling use-cases will continue to emerge.

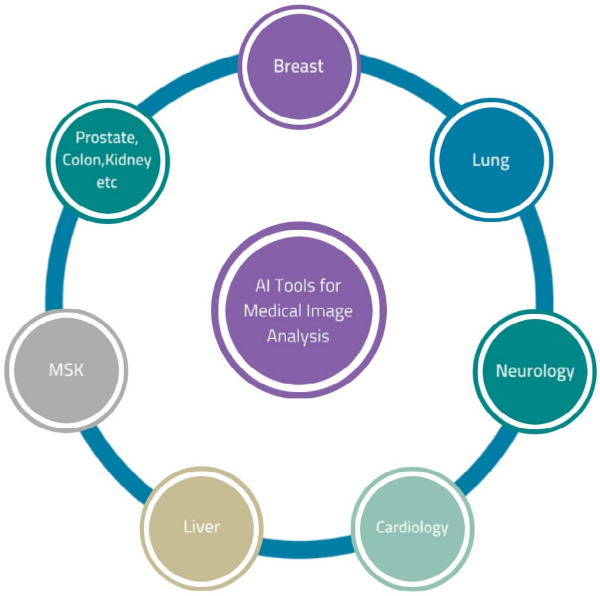
Machine learning itself is not a solution to the many challenges facing the medical imaging industry, merely an enabler. If the technology is to make a tangible impact, algorithm developers need to identify compelling use-cases where the use of AI can be shown to both improve clinical outcomes and deliver a clear return on investment for health care providers. Moreover, the technology needs to be fully integrated in the existing user interfaces and workflows found in radiology departments, both working in the background to augment radiologists' knowledge and efficiency, and readily accessible when specific tools are needed.

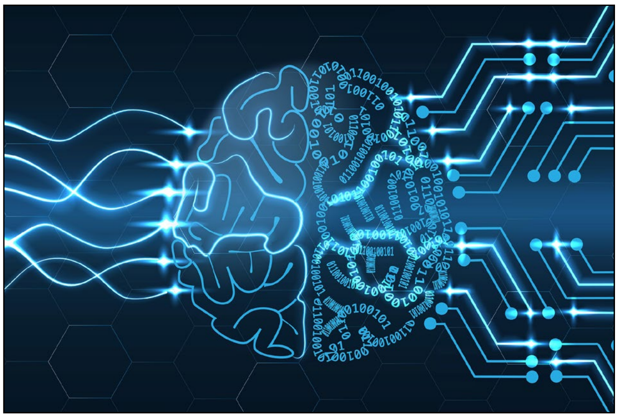
The most established market for machine learning in medical imaging is breast cancer screening, and most breast imaging centres in the US already use some form of breast cancer detection software. However, to date, the market has largely failed to take-off outside of the US, mainly due to the limitations and poor performance of early generation AI-based products. That is poised to change in the coming years, following the introduction of deep learning-based solutions with improved detection accuracy and predictive capabilities. Deep learning has sparked a renewed interested in cancer detection software, both in the US and internationally, and health care providers who had previously dismissed it are now taking a second look. Similarly, machine learning is increasingly being used to detect and quantify lung nodules, particularly in the US where the introduction of a population-based lung cancer screening program and the associated increased in scan volumes has placed additional demands on radiologists. More countries are expected to roll-out lung cancer screening programs, further stimulating demand for machine learning solutions.

Today, cancer detection software is mostly used as a second-read tool, serving as a "second pair of eyes" to ensure that radiologists don't miss a suspect area on an image. As the detection accuracy of the latest generation of deep learning-based solutions continues to improve, alongside the introduction of advanced functionalities such as predictive scoring for the likelihood of malignancy, the argument for using detection software for the primary read is getting stronger and is expected to become a reality within the next five years.

Neurology is another early adopter of AI in medical imaging, with two distinct use-cases; (1) the detection of stroke and intracerebral haemorrhage (ICH) and (2) volumetric post-processing solutions for the detection and quantification of imaging biomarkers to support with the diagnosis and treatment planning for neurological diseases and disorders. In January 2018, the American Heart Association (AHA) introduced new guidelines for the treatment of stroke, based on the results of two important trials, DAWN and DEFUSE 3. The new guidelines extend the treatment window for select patients with salvageable brain tissue, as identified through MR or CT perfusion imaging, to receive mechanical thrombectomy from six hours to 24 hours after their stroke. This has led to a surge of interest in AI-based image analysis software for early detection and diagnosis of stroke. Several companies have released products that can detect stroke from an initial CTA scan (or perfusion imaging) and immediately notify a neurologist/interventionalist, leading to faster treatment and better patient outcomes. In addition to the improved clinical outcomes for patients, there is a clear return on investment for

Figure 5 Clinical Applications for Machine Learning in Diagnostic Imaging





health care providers from using stroke detection software, as the early detection and treatment of stroke can reduce long term care costs. Moreover, thrombectomy procedures are typically well reimbursed.

In cardiology, there is increasing use of non-invasive imaging techniques for the diagnosis of coronary artery disease (CAD), the world's biggest killer, as alternatives to an invasive coronary angiography. This is driving demand for AI-based diagnostic tools for use with cardiovascular MRI (CMRI), coronary CT angiography (CTA) and echocardiography. Of particular interest is the use of machine learning to calculate fractional flow reserve CT (FFR-CT). FFR-CT has been shown to reduce the number of unnecessary referrals for an invasive coronary angiography; however, the complex computational models used to calculate FFR-CT require large amounts of processing power and it can take several hours to calculate the results. With advanced machine learning techniques and cloud compute, the results can be obtained in seconds. In echocardiography, AI-based quantification software is increasingly being used to automatically calculate measurements such as ejection fraction, which can potentially reduce the time per exam by up to 30 minutes. Moreover, the results are repeatable and not prone to inter- and intra-observer variability.

Whilst there is a dizzy array of applications for machine learning in medical imaging, health care budgets are under pressure globally and providers will need to prioritise their AI investments. Vendors must clearly articulate the value proposition of their machine learning solutions, ideally through a combination of improved clinical outcomes and a demonstrable return on investment (ROI).

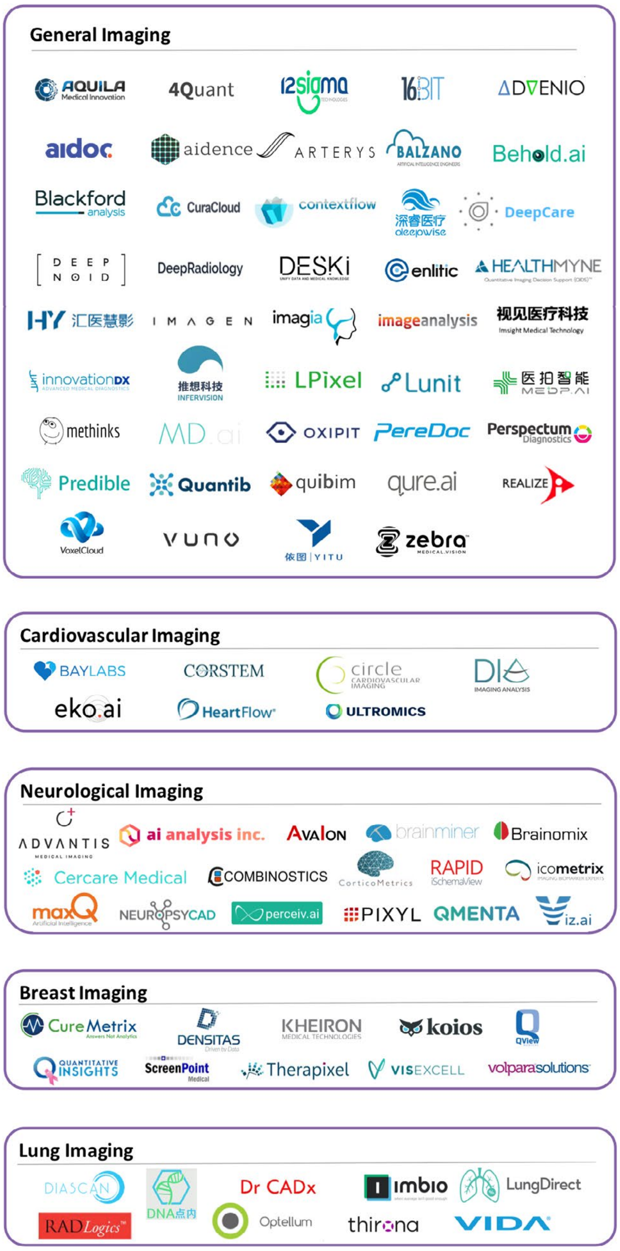
Prediction 4:

Medical imaging AI will transition from academic research to commercialization.

The improved performance of deep learning over early generation artificial neural networks has led to renewed interest in machine learning for diagnostic imaging. The number of published research papers on this topic has escalated in recent years, covering a wide range of novel use-cases across all aspects of the diagnostic imaging workflow, from tools that provide automatic feature detection, segmentation and quantification, to decision support tools that provide contextual patient information extracted from EHRs, pathology reports and other siloed data sources, to automated diagnosis tools that suggest probability-based differential diagnoses. The findings from these research papers suggest that deep learning can be applied to a wide variety of medical pathologies and across the full spectrum of image acquisition hardware, from x-ray and ultrasound to advanced imaging modalities such as CT, MRI and nuclear imaging.

In parallel to the extensive research activity, the first wave of commercialized deep learning-based solutions for diagnostic imaging is now entering the market and gaining initial acceptance, both with radiology luminaries at the forefront of clinical innovation and forward-thinking radiology practices who recognise the potential for AI to take on repetitive and time-consuming tasks, leading to enhanced productivity and a competitive advantage. Most of these first products to market are from start-up companies and new market players, often spin-outs from academic research. There are over 100 specialist developers of machine learning algorithms for medical imaging applications and collectively these companies have received over $1 billion in capital investment, primarily from venture capital and private equity firms. Many of these medical imaging AI start-ups are very well funded and have successfully completed later-stage funding rounds to enable them to bring products to market and scale their activities.

Figure 6 Medical imaging AI specialists by clinical application



THE EXPANDING VENDOR ECOSYSTEM

More recently, the incumbent medical imaging vendors have ramped-up their AI activities, with an initial focus on workflow and reporting tools but with longer-term ambitions to release AI-based diagnostic tools. Whilst initially starting out with software applications for use with their PACS and advanced visualization platforms, the imaging modality vendors are also leveraging development in edge computing to embedded machine learning algorithms in imaging equipment, so that imaging data can be processed at source. Additionally, several of the world's technology giants, including Facebook, Google, Tencent and Alibaba, have started to apply their AI expertise to medical imaging, leveraging their huge investments in machine learning for consumer applications such as virtual assistants and autonomous vehicles. Over the coming years, the combined R&D firepower of the expanding medical imaging AI ecosystem will accelerate the pace of product development, and radiologists will have a rapidly expanding array of AI-powered workflow and diagnostic tools at their disposal.

NO VENDOR CAN DO IT ALONE

With so many use-cases for machine learning throughout the medical imaging workflow, and across numerous clinical applications and imaging modalities, strategic partnerships are king, both for health providers and technology vendors. Currently, most vendors offer only a handful of AI-based solutions, which are typically focused on a specific application area, e.g. breast, lung or cardiology, which limits the utility of machine learning for most generalist radiologists who require a comprehensive "analytical tool kit" with a broad portfolio of algorithms. It's a daunting task for a single company to create such a library of algorithms, comprising tens and potentially hundreds of analytical tools. Partnerships will be essential to create the end-to-end solutions that meet the needs of most radiologists. No company can do it alone.

For technology companies developing machine learning solutions, strategic collaborations and partnerships with healthcare providers are essential. Not only do they provide vendors with academic and clinical domain expertise, but they also give access to annotated imaging data to train and validate machine learning algorithms – one of the biggest challenges for most algorithm developers. By working closely with providers, vendors can identify the greatest pain-points for clinicians, be it workflow-related or part of the clinical decision-making process, and hence the areas where machine learning can add the greatest value.

The incumbent healthcare technology vendors will need to collaborate with AI specialists to remain competitive in an AI-driven health care market. To that end, strategic distribution and technology licensing partnerships are increasing and the first online AI marketplaces are now open for business. These vendor-neutral ecosystems provide AI-based tools and applications from a variety of third--party software developers, alongside solutions from the platform owner, much like an app store for radiology. Merger and acquisition activity will increase, with the established vendors snapping-up medical AI start-ups to fill gaps in their technology portfolios.

Prediction 5:

Machine learning will benefit all medical imaging 'ologies'.

Whilst radiology is at the forefront of the use of machine learning in healthcare, other medical imaging 'ologies' will follow suit in the coming years. Each is at various stages of machine learning readiness, in terms of digitalization, investment in AI R&D and physician acceptance, as summarised in the table below.

OPHTHALMOLOGY

Across the various medical imaging specialties, ophthalmology is second only to radiology in terms of machine learning adoption. There are numerous potential applications for machine learning in the assessment of various diseases, including cataracts, glaucoma, age-related macular degeneration and diabetic retinopathy. The latter is one of the most promising use-cases and in April 2018, IDx became the first company to obtain US FDA authorization to market an AI-based diagnostic system for the autonomous detection of diabetic retinopathy. More than 30 million Americans have diabetes, and an estimated 24,000 lose their vision each year from diabetic retinopathy, a complication of diabetes. The IDx system can be used in primary care settings to enable early detection of retinopathy, which can prevent vision loss and blindness.

PATHOLOGY

Whilst most radiology departments transitioned from film to digital images more than two decades ago, pathology is still in the early stages of digitalization and today most pathologists

Figure 7 Machine learning readiness by imaging speciality

Clinical Speciality	Key Uses for Machine Learning	Machine Learning Readiness
Radiology	Workflow efficiency and clinical decision support	High
Dermatology	Detect skin cancer and diagnose malignancy of moles	Low
Ophthalmology	Detect and diagnose disease, such as diabetic retinopathy	High
Pathology	Detect and diagnose disease from tissue samples	Low
Oncology	Cancer diagnosis, prognosis and treatment planning	Mid
Surgical	Endoscopic image analysis	Low

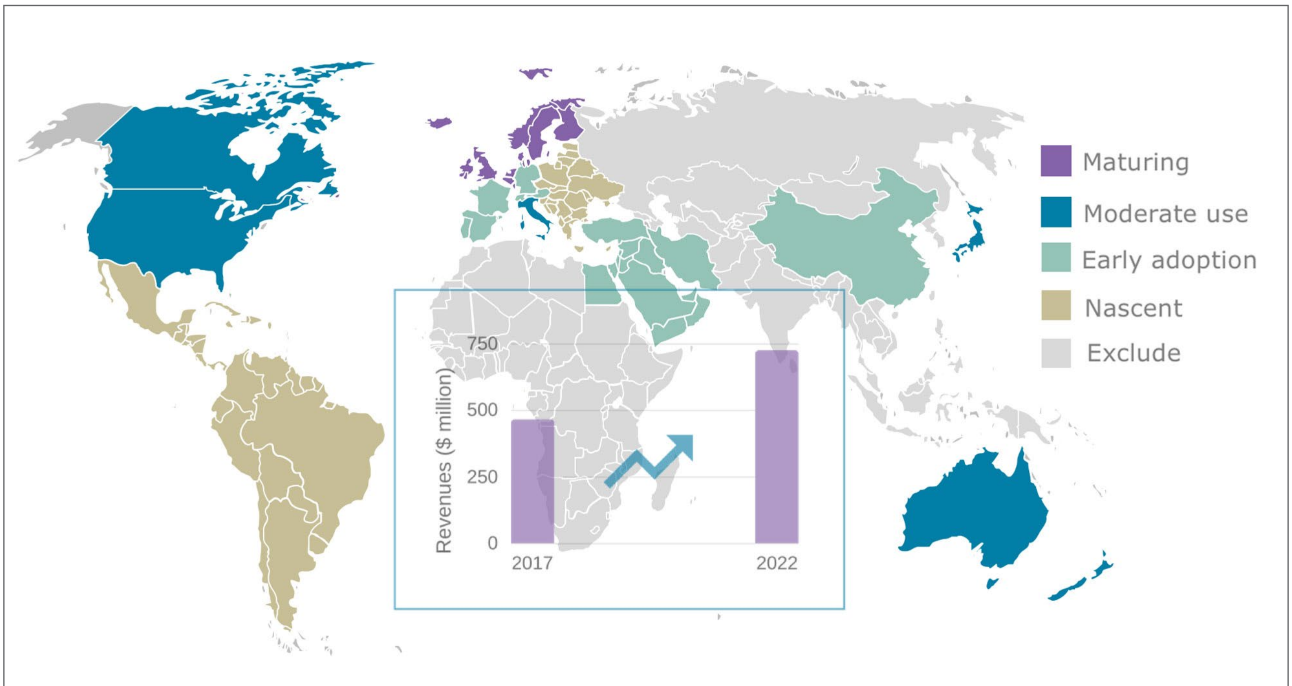
still study tissue samples on glass slides using microscopes and other specialist laboratory equipment. That said, forward thinking pathology labs have begun to transform their operations by shifting away from traditional microscopes to the digital equivalent - high-resolution imaging and virtual microscopy.

In the US, digital pathology was initially used for research and remote consultation but following FDA approval of Philips Healthcare's IntelliSite Pathology system in 2017, whole slide imaging may now be used for primary clinical diagnosis. This can yield attractive clinical and economic benefits, including increased pathologist efficiency, reduced glass-handling and associated real estate costs. Digitalization also introduces the possibility to leverage AI and when combined with the recent developments in deep neural networks, there is a growing interest and significant opportunity to deploy machine learning within pathology, although this is currently largely untapped potential.

Digital pathology is yet to be adopted on a mass market scale and most countries are in the early adoption or growth phase of market development. One of the biggest challenges for pathology departments is justifying the investment and quantifying the economic benefits to shift to digital infrastructure, particularly when many of the gains extend beyond the pathology department itself. More specifically from a cost perspective, overcoming the inherent technical and storage issues created from digital slide images. High annual slide volumes and large image file sizes put significant burden on health IT infrastructure for moving and managing this data. For this reason, usage-based storage services are expected to be an increasingly popular solution.

The use-cases for machine learning in digital pathology are broadly the same as for radiology – workflow tools for labour efficiency gains and diagnostic support tools. In particularly, there is growing interest in leveraging machine learning for better quantitative modelling of disease appearance to improve diagnostic and prognostic accuracy and to predict treatment outcomes. Over time, quantitative imaging biomarkers extracted from diagnostic imaging (radiomics) will be combined with quantitative biomarkers of pathophysiology and other sources of patient data for better prognostic prediction of disease progression. This in turn will enable improved treatment planning and better patient outcomes.

Figure 8 Digital pathology market maturity and growth forecast



Prediction 6:

Health providers will leverage data hubs to unlock the value of their data.

As health care becomes more data-centric, health systems need effective strategies for data management, with enterprise-level processes for storing, securing and analysing data from diverse sources across their organisation. Some of the many benefits include:

- Create big data for population health management - define patient cohorts, stratify patients by their risk of developing disease and deliver care targeted to the individual needs of those patients
- A more complete and longitudinal view of the patient for more accurate diagnosis and treatment planning
- Improved collaboration across multi-disciplinary teams
- Efficient data throughput for advanced machine learning
- Reduced operational costs

Today, a large percentage of health data remains siloed in disparate systems and the data cannot be fully utilized. Electronic medical records (EMR) have made significant inroads by creating centralised repositories for financial and administration data and basic patient information, but most clinical data still resides in departmental systems, such as PACS, laboratory information systems and clinical care information systems, each with its own IT infrastructure. Even within departments there can be multiple IT systems. For example, larger radiology departments may have a PACS for routine clinical use and a separate system with de-identified patient data for research use, such as developing and training machine learning algorithms. Due to the lack of interoperability between these systems, many hospitals are consumed by the vast amounts of data held in these silos, which is often viewed as an expensive commodity, rather than an asset.

To fully capitalize on the value of their data, hospitals are beginning to invest in infrastructure for enterprise data hubs and big data management solutions. These centralised data repositories can quickly provide diverse clinical users with the information they need, when they need it, helping providers to unlock the full value of their data. By emphasising data delivery rather than data storage alone, data can be leveraged for multiple uses and applications.

Figure 9 Centralised clinical data hubs

The industry-wide push towards more integrated care, along with the advent of machine learning that demands greater interoperability of data, is driving focus on centralising clinical information into a single platform to form a base for all diagnostic and acute clinical care management. By moving to an enterprise data hub for clinical content management, health providers will improve access and interoperability of both structured (e.g. DICOM) and unstructured data across multiple clinical applications, enabling machine learning algorithms to produce richer and deeper insights. For example, machine learning tools can provide radiologists with contextually relevant patient information alongside the scan at the time of the primary read, leading to faster and more accurate clinical decision making.

Prediction 7:

Developments in IT infrastructure will accelerate the performance of medical imaging AI systems.

Advanced machine learning techniques such as deep learning require high performance IT infrastructure to support the massive amounts of data needed. GPUs are particularly well suited to image processing, such as the convolutional neural networks that are being applied to many medical imaging applications, due to their massive parallel processing performance. The latest generation of GPU technology has several thousand processing cores and delivers over 100 teraflops of deep learning performance.

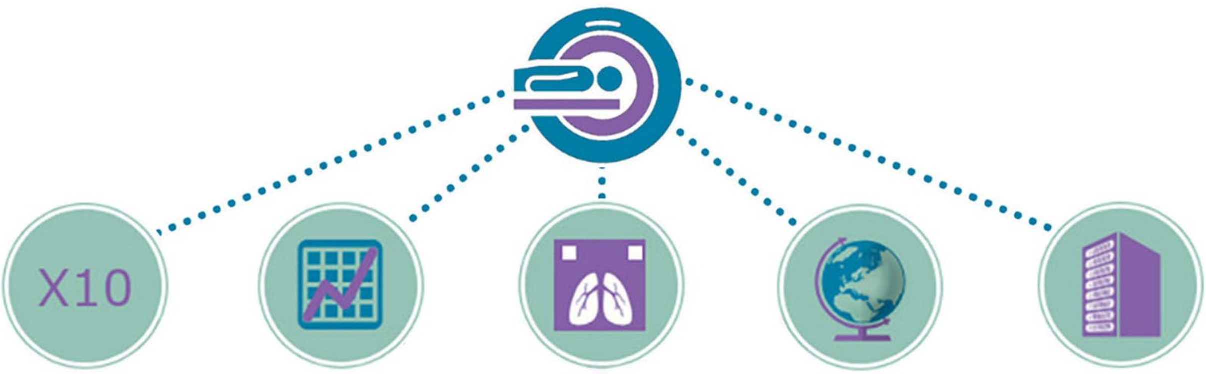
Hospitals around the world are establishing clinical data science groups to support their transition to data-driven health care and are investing in on-premise GPU-accelerated servers to develop and train machine learning algorithms. This requires a sizeable capital investment and hence it is important that the networking and storage infrastructure does not create bottlenecks that leave the GPU servers idle. Moreover, high performance infrastructure will enable faster machine learning results and finer tuning of the algorithms for accuracy. Scalable, AI-ready infrastructure is also of paramount importance when these home-grown algorithms are deployed in clinical practice and as providers invest in the expanding range of off-the-shelf machine learning solutions. Particularly when multiple machine learning applications run simultaneously, placing additional demands on the infrastructure.

ADVANCED STORAGE FOR MEDICAL IMAGING AI

Alongside high-performance GPU servers, one of the biggest considerations for successful medical imaging AI deployments is the storage. All-flash storage is gaining acceptance over legacy hard disk drives in health IT infrastructure due to the lower read/write latency, higher throughput performance, and improved scalability. Many health care organizations started their transition to all-flash storage with their electronic health record (EHR) and enterprise analytics platforms and are now extending their use of flash to departmental clinical systems, often starting with medical imaging. Flash is particularly well suited to medical imaging due to the technology's ability to serve the concurrent needs of multiple users and applications. For example, by ensuring data hungry machine learning applications do not compromise the day-to-day performance of the imaging IT platform.

Falling flash storage prices combined with secondary economic benefits such as a smaller footprint, lower energy costs, and fewer servers to license mean that flash can be used for primary storage beyond only mission-critical applications. In addition to the IT benefits — resiliency, durability, performance, and optimized virtualization — flash storage can help change how clinicians practice medicine because they will have faster access to health information and clinical insights than ever before.

Figure 10 Factors driving the need for increased image storage capacity



Imaging volumes will continue to increase, by **5-10%** annually in the US	3D breast images (DBT) are **10 times** the size of conventional 2D (FFDM) images	There are **600M+** diagnostic imaging procedures in the US annually	Globally, annual storage of diagnostic images is already in the **hundreds of petabytes** range	US hospitals typically store **several terabytes** of imaging data annually

At Signify Research we are passionately curious about Healthcare Technology and we strive to deliver the most robust market data and insights, to help our customers make the right strategic decisions. We blend primary data collected from in-depth interviews with technology vendors and healthcare professionals, to provide a balanced and complete view of the market trends.

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