A Review of the Impact of Deep Learning in Practical Contemporary and Near-Future Applications in the 21st Century

# Abstract

# 1. Introduction

## Overview

Deep learning is a type of neural network-based machine learning that involves using a set of nodes, split into input nodes, hidden nodes and output nodes with a calculation step with nodes being formed into a layer (Q. Zhang et al., 2018). A typical deep learning network is feed-forward in design with input nodes feeding into hidden nodes, feeding the next hidden nodes with connections made between each layer’s nodes to the next. This repeats for *x* number of hidden layers until the data is fully transformed and passed to the output nodes. Weights, mathematical coefficients assigned to each node determines the scale of transformation with different mathematical functions available for each layer. Typically, a logistic function which forms a sigmoid curve is used, though recent developments show that there are more efficient alternatives:

In recent years, the most popular nonlinear function used here is the rectified linear unit (ReLU) f(z) = max{0, z} which typically learns much faster in multi-layer deep neural networks than the more conventional hyperbolic tangent and logistic sigmoid function (Xiao et al. 2018, p. 4)

The process of the mathematical calculations is usually not directly observed, giving deep learning a black box approach to development where only the inputs and outputs are regularly checked. Deep learning is differentiated as a neural network with many hidden layers, typically at least 6-10, of nonlinear processing units for feature extraction and data transformation. There are two specialised types of deep learning neural networks in common use; recurrent neural networks in which data flows in any direction, used for language modelling and convolutional deep neural networks which are mostly used for computer vision and automatic speech recognition. The great number of mathematical connections between nodes means exponential increases in complexity when expanding the number of layers and/or nodes which makes deep learning initially very computationally expensive when compared to traditional algorithms. A large proportion of the computational power used will not necessarily be used within the calculations performed on a prepared network but the training of a network, the length of which is directly tied to the number of connections within a network. A fully trained network is often more efficient computationally, faster and more accurate than traditional algorithms.

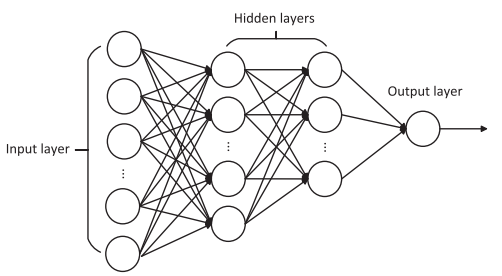


Fig 1 – Example Structure of a Neural Network, image taken from Xiao et al. (2018)

## Machine Learning Methods

Learning can be supervised, semi-supervised or unsupervised. Supervised learning consists of teaching a network to recognise patterns based on learning the values of pairs of input and output values fed to the system. The network will adjust to these values, called a training set, to prepare it for receiving novel data. In theory a trained network will be able to adjust itself to recognise novel data presented to it and accurately calculate the correct result intended by the training process. Semi-supervised learning is a technique in which unlabelled data is mixed with the training data, which can improve the learning accuracy of a network. A problem with supervised learning is that often a network may be trained too specifically towards training data, meaning it cannot identify novel examples introduced, only trained examples. In contrast, unsupervised learning does not have predicted accuracy due to the lack of concrete examples from which the network can learn which can result in greater difficulty training. However a network will still be able to detect and learn patterns and similarities between data sets available to it. A common method of training is back propagation, a technique that calculates gradient descent, adjusting weight values based on the gradient of the loss function, effectively reducing the error rate over time. It works on a repetition of a two-phase cycle, propagation and weight correction. An estimation of the correct output using a loss function is compared to the result of one network iteration, with the errors propagated back through the network, updating each weight relative to its contribution to the original output. Alternatives to back propagation exist (Rios and Sahinidis, 2012) using derivative-free algorithms but are seldom in use.

# 2. Methods

An initial search was performed on the University of South Wales Library portal, looking for articles associated with deep learning. For this purpose, I used multiple searches using the phrase “deep learning” with additional key words of “medical”, “scientific”, “commercial”, “industrial” and “applications”. An initial selection process involved selecting articles based on their relevance to deep learning. I obtained a PDF copy where available and downloaded any associated articles I could find that were presented. I found a large quantity of articles available, particularly on the website “ScienceDirect” and downloaded a few dozen linked articles. Going further, I searched directly on the ScienceDirect website for articles on deep learning and found many. I then followed this up with a set of various searches using similar search terms as used previously on google scholar, JSTOR, arXiv and Jurn. JSTOR unfortunately has a paywall preventing me from using that source but I obtained many useful articles from google and Jurn. Of note several of these journal search engines linked to each other and my searching involved going back and forth between different websites. This initial data gathering was to find a great deal of material on the subject I am covering, followed by a later culling of inappropriate or poor sources.

My initial gathering of articles en masse yielded 93 articles of interest about deep learning. All articles gathered mention deep learning within the title or the abstract. Approximately 20 articles were carefully picked out one by one in a manual fashion with an eye for quality, most notably with Litjens et al. (2017), a review paper of medical image analysis. I selected a Science article (Hinton, 2006) on reducing dimensionality due to its reference in other papers even though it is more than a decade old due to its famed relevance to the field. I also considered that Science is one of the best academic journals available. This was a factor that weighed into my selection of a Nature article (LeCun, Bengio and Hinton, 2015), the most cited scientific journal in the world. Curiously enough Hinton features in both articles. The remainder of articles were collected through links to associated papers.

A sift through the articles resulted in 24 articles dropped from my selection due to one of the following reasons:

* The article not once mentions deep learning in the main body of the text, nor neural networks
* The article does not go into sufficient detail to be useful or coverage of the subject is very low
* Specific applications are not referenced, or the application is a methodological approach rather than a practical application

The remaining 69 articles were read, though I did not thoroughly read through deep learning methodology in every article as it was often near identical in most articles. An exceptional article, involving a study of spindle power data from mining tools, does not refer to deep learning but only neural networks. I decided to include this based on its potential future applications. All other articles explicitly refer to deep learning at a good level of detail. An example of an article culled due to its lack of applicability to the topic was an article on weighted kappa loss functions used for optimisation of deep learning, culled due to its lack of practical application.

# 3. Discussion

## 3.1 Scientific Applications of Deep Learning

Reconstruction of cosmic ray induced air showers has been performed using deep learning (Erdmann, Glombitza and Walz, 2018). Using simulation of ground-based particle detectors on a regular grid of neural network nodes, it was found that resolution of higher cosmic ray energy was improved. The practical applications of this are not clear, particularly given the lack of real data used which would have greatly improved the work.

Of greater interest is a deep learning approach called deep filtering. Initially using simulated data, the authors had previously published an article on their simulated data findings (George and Huerta, 2018b), with real LIGO data used in this example. This uses Laser Interferometer Gravitational-Wave Observatory (LIGO) data to help identify gravitational waves (George and Huerta, 2018a). The techniques are used for detection and parameter estimation of gravitational waves from binary black hole mergers using continuous data streams from LIGO detectors. Compared with matched filtering, an optimal filter for maximising the signal to noise ratio in the presence of stochastic noise, deep filtering achieved similar sensitivities and a lower error rate while being more computationally efficient and more resilient to glitches. This allowed real time processing of weak time-series signals in highly variable levels of noise with low resource use and best of all, a method of detecting new classes of gravitational wave sources that may go undetected with current algorithms in use. In conclusion the authors advise that deep filtering be used in addition to the current matched filtering techniques in LIGO. It is also commented that the scalability of deep learning allows overcoming the curse of dimensionality and the use of potentially, terabytes of training data. Such extensions the authors state, could be extended easily to perform millions or even billions of training templates over the entire range of parameter space that is beyond the ability of extant algorithms. However, it must be noted that the development of deep filtering was conducted on supercomputers by the Blue Waters sustained peta-scale computing project, so any attempt to extend the use of deep filtering would require an expansion of supercomputer capacity at LIGO.

## 3.2 Medical Applications of Deep Learning

The primary medical application of deep learning is in medical image processing. This includes the use of predicting patient conditions based on medical history and diagnosing tumours from scan results. Medical image analysis has had more than 300 papers alone surveyed in one review paper (Litjens et al., 2017). Of the papers surveyed, application areas were amongst others listed as neuro, retinal, pulmonary, digital pathology, breast, cardiac, abdominal and musculoskeletal systems. Pathology and brain studies were the most common with just over a third of the papers concerning those topics. The topics least studied were bone and retinal cases, indicating a possible gap in the knowledge of deep learning imaging techniques conducted on bones and retinas. A conclusion made is that deep learning has pervaded every aspect of medical image analysis in a short space of time, with 242 papers published in 2016 or within the first month of 2017. Convolutional neural networks, a deep learning network used widely in image processing dominant in terms of performance, but the choice of architecture is not the most important component of a good solution. To improve the chances of a successful solution, it is recommended to implement effective pre-processing including normalisation and data augmentation. A final recommendation is to optimise the learning and dropout rates of the network but the authors caution that the correct level of optimisation is effectively a trial and error process. For future work in the medical image analysis field, greater public access to collections of images for training sets would allow research to be conducted more easily and labelling for the image data which is far rarer than the images themselves. To conclude recommendations, it is not only the images that contain useful data, but the leveraging of patient data based on history, age, demographics amongst other factors. Looking forward, the authors identify a key area that is receiving renewed interest, unsupervised learning and state that while deep learning is often black box in nature, due to the sensitivity of life and death situations with medical technology, network development should attempt to make clear what intermediate layers of a network respond to.

A journal article discussing deep learning-based bone-age scanning (Spampinato et al., 2017), noted as a subject for which there is a gap, notes significant progress with deep learning techniques. The results were “an average discrepancy between manual and automatic evaluation of about 0.8 years, which is state-of-the-art performance.” (Spampinato et al., 2017). When compared with other studies performed, the performance was superior to all other models assessed but with the caveat that Spampinato et al. were unique in using a public dataset and made their implementation fully available.

Classification of 4 different types of brain tumours has been achieved using a deep neural network classifier (Mohsen et al., 2018), resulting more accurate results (96.97%) than other AI methods used, including K-nearest neighbour (between 86.36% - 95.45%), sequential minimal optimisation (93.94%) and linear discriminant analysis (95.45%). While the results are positive, the sample size was 66 human brain MRIs which is not in my opinion large enough to properly test deep learning. Using similar methods, segmentation of brain tumours in scans have been automated with deep learning (Zhao et al., 2018). However, unlike many other studies including Mohsen et al. (2018), the authors noted that they were competitive with other techniques used but not clearly superior with their implementation.

Cancer prediction has been implemented using gene expression data (Xiao et al., 2018), specifically involving Lung Adenocarcinoma, Stomach Adenocarcinoma and Breast Invasive Carcinoma. Multiple machine learning models were implemented with the results ensembled from the outputs of the classifiers used. Results concluded with an increase in prediction accuracy with all tested RNA-sequence data sets when compared with the best single classifier or a majority voting algorithm. A major benefitted noted is the improvement of computational time required and the reduction of dimensionality of the data. Mitosis detection, a factor in predicting breast cancer (Saha, Chakraborty and Racoceanu, 2018) has been implemented with deep learning also.

Tumour contours are the outline of a tumour within a radiological scan, requiring manual work by a doctor to mark. In a study on the performance of atlas and deep learning basic automatic contouring for lung cancer (Lustberg et al., 2018), the median time reduced in contouring organs at risk was 7.8 minutes for an atlas-based contour and 10 minutes for a deep learning contouring operation, compared to an average time of manual contouring that takes 20 minutes by a human. These results give in effect a 39% reduced time for contouring with an atlas and a 50% reduction of time spent using deep learning. This does not consider the impact of a human doctor being able to leave a machine to conduct contouring in its entirety without oversight, therefore the 50% reduction in time would occur in a human supervised contouring operation. The study discusses the impact that auto-contouring software could have in the near future, concluding that time can be saved for radiologists who if in doubt of the automated results could perform a manual contouring operation instead.

Lesion detection in the context of diabetic retinopathy, a preventable side effect of diabetes has been shown to be automated using deep learning (Orlando et al., 2018).

A review paper on the pharmaceutical and bioinformatic applications of deep learning states that “There is a huge potential in applying DNNs in the process of drug discovery, design and validation that could improve performance and greatly reduce costs” (Pastur-Romay et al., 2016). This is due to the scale of the data involved with testing new drugs. An example study mentioned that involved 150,000 substances was criticised for having too small a sample size, which is a testament to the enormous scale of data-driven challenges in drug development.

## 3.3 Commercial Applications of Deep Learning

Deep learning plays a significant role in data mining using big data (Q. Zhang et al., 2018). As examples of the scale, Flickr and Google process approximately 3.6 terabytes of data and 20 petabytes every day respectively. The National Security Agency in the USA estimates that 1.8 petabytes of information are actively collected on the internet each day. The central challenge of dealing with such a volume of data is to extract the useful information out which deep learning is effective at achieving. Q. Zhang et al. note that while contemporary deep learning techniques are capable of learning features on extremely large datasets, in the future with the potential of computational power increases slowing down and a simultaneous increase in the size of data sets, it will be more difficult computationally, even taking into consideration the effectiveness of deep learning techniques.

A particularly tricky commercial challenge is recommending items to a user of a service. This can be very difficult with items that either have few ratings, called an incomplete cold start or none, a complete cold start (Wei et al., 2017). Using Netflix rating data, Wei et al developed several models using a deep learning technique and compared their results to a set of baseline examples. Their results indicated a significant increase in performance, indicting that their IRCD-ICS model performed more than twice as well as the slowest baseline model. A reduction in dimensionality of the data is extremely beneficial to recommendations as each recommendation is a factor of many ratings of associated items, which can in turn be associated with other items and so on. The deeper the links go into associated items, the greater number of dimensions involved in calculations.

## 3.4 Automotive Applications of Deep Learning

Automotive applications include the use of self-driving cars, using deep learning algorithms that can accurately detect the presence of vehicles and road lanes. Detecting pedestrians via their head pose and body orientation, a subset of automated human activity recognition, is tackled by deep learning (Raza et al., 2018). Because the orientation of a head and torso is greatly predictive of human movement, correct estimates are of great use for automobiles avoiding collision. Raza et al. in experiments achieved a mean accuracy of 0.91 and 0.92 for head pose and full body estimation.

An approach for detecting traffic accidents from social media data has been demonstrated (Z. Zhang et al., 2018) using the social media tweets from Northern Virginia and New York City. Deep belief networks (DBN) and long short-term memory were used, with an overall result of 85% accuracy when using a DBN. It was found that 66% of accident related tweets can be located by the local freeway accident log and that more than 80% are directly tied to abnormal traffic data obtained through loop feedback, a local method of obtaining traffic data. Some bias is noted as well as the characteristics of the twitter users having influence, but the strong correlation of abnormal traffic data suggests a definitive link. Of note is that the usage of tweets picks up accidents that are not reported to the police so while the data is not an excellent primary source, it is an effective secondary source for information that is otherwise unavailable to the authorities. With the capability for real-time accident monitoring, social media monitoring for accidents could be a viable as a low-level source for plugging gaps in the real-time knowledge of the local police force so long as they operate with caution over the fickle nature of tweets.

Obstacle detection remains an issue for self-driving cars and for autonomous robots (Dairi et al., 2018). Using a vision-based obstacle detection system Dairi et al used deep Boltzmann machines with auto-encoders to greatly reduce the dimensionality of data. Deep learning algorithms use a large quantity of data and processing power, particularly for frame by frame processing. In contrast to a traditional deep learning system that simply has an output layer, auto encoders formed the output layer, directly taking the output and then reducing its footprint. In field testing it was discovered that an accurate way of determining the number of incidents of obstacles in stereovision was strongly correlated with the density of the surrounding scene. Additionally, obstacle detection was treated as an anomaly detection problem, with outliers identified, confirmed as obstacles and fed to a tracking system. False alerts were deal with through the improvement of accuracy by using two models. These models were used, set and trained for open, free scenes and busy, cluttered and urban scenes respectively. The combination of these two models allowed a more accurate model that was able to deal with fuzzy situations, which are particularly common in very busy urban areas. Results proved the reliability of their system in detecting obstacles and in conclusion they noted that a high level of noise reduction and superior image quality was the primary concern in achieving reliable results.

The use of cloud computing in managing an in-car camera system has been developed to test the feasibility of having an online based deep learning network coupled to a local camera that feeds captured images online (Chen, Lee and Lu, 2017). The network is trained in the cloud where computing resources are more available. An interesting note in the article is that a technique named deep compression is used to reduce the size of an Alex Net implementation from 240MB to 6.9MB without any accuracy loss. This technique which uses pruning, trained quantization and Huffman coding (Han, Mao and Dally, 2016) has been used to compress deep learning networks from between 35 times smaller to 49 times smaller than their original size. The central conclusion was that GPU hardware in the local environment is critical to process images due to its 20 times faster processing compared to a CPU.

## 3.5 Language Applications of Deep Learning

Deep learning has received a lot of interest due to its applications with translations and language processing (Costa-jussà et al., 2017). This domain includes both natural language processing and speech recognition. The curse of dimensionality occurs in language processing as each word or symbol is best represented as a continuous vector (Choi, Cho and Bengio, 2017). These vectors are encoded with multiple dimensions of similarities to other words or symbols to represent the links between words that are tied together in a language. Choi, Cho and Bengio separated words into three tokens; digits, proper nouns and acronyms. Digits were used to identify individual characters within the source material and the target sentence. Nouns are shared in many languages with a common meaning such as “cat” in English and “chat” in French. Before deep learning, translation services often provided broken translations because they used a map of noun to noun exchanges but lacked the ability to work out subtleties in meaning. A similar case was used with deep learning except for using variables to track and place its position in a target output sentence. Acronyms are a special case because they differ language to language for which they used lists of associated acronyms for different language pairs. Finally, a rule dictionary was developed to replace generated symbols with the correct translated symbol. In summary all these techniques combined provide contextualisation and symbolisation to improve translation quality.

Further developments also including Bengio’s work (Firat et al., 2017) include using multilingual translation. In this work deep learning techniques applied over a set of ten different language pairs were more successful than the same techniques applied to only one language pair.

# 4. Conclusions

The predominant theme of deep learning is that it greatly reduces time spent performing tasks when using a fully trained network. This is multifaceted, through a direct reduction in computational time and a reduction in dimensionality of the data. Multiple studies (George and Huerta, 2018b; Hinton, 2006; Choi, Cho and Bengio, 2017) reference the potential of tackling the curse of dimensionality, a major factor that exponentially increases the computational power required to work with very large datasets. The studies on deep filtering for LIGO (George and Huerta, 2018a), (George and Huerta, 2018b) are an example where extreme amounts of data can be used in real time due to the benefits of deep learning albeit with a supercomputer. When the pharmaceutical study on big data (Pastur-Romay et al., 2016) is considered, it has a prescient statement that the contraction of Moore’s law means the expansion of algorithms that reduce computational power through deep learning will likely become a necessary staple of projects that involve large datasets. Q. Zhang et al. (2018) are more negative claiming that even with the efficiencies of deep learning, there will still not be enough capability to keep pace with the increases in size of big data, which I disagree with due to the ability for specialised hardware to make up any shortfall. Other articles are more positive and see a maintenance of Moore’s law into the future (Pastur-Romay et al., 2016), but I think there will be a continuation of the current trend for a gradual slowdown. Even taking a slight reduction in Moore’s law into account as hinted at in this article, it’s likely deep learning will be able to simulate a human brain sized network in terms of the number of neurons within the next few decades as an example of increasing computational power, though in terms of connections we’re still far, far away from achieving such a level of detail. In any case, it appears that if Moore’s law does break, there is a great scope for deep learning to make up the shortfall in computational power with more efficient processing. Such a change would lead to chip architecture based around deep learning networks in the same manner that GPUs have been spun off the CPU for a dedicated processing task.

The use of specialised architecture may be necessary regardless of Moore’s law when the vast scale of big datasets such as commercial or astronomical datasets is considered. LIGO data required a supercomputer to be processed in a deep learning network (George and Huerta, 2018b). The authors state openly that terabytes of data can be used as a training set for training a deep learning network relatively easily compared to a traditional algorithm, a task only currently capable to be performed in real time using the world’s most powerful computers available. Q. Zhang et al. (2018) also state the need for increasingly powerful machines to process large datasets in real time, particularly due to the estimated impending 35 zettabyte global size of big data in 2020, equivalent to 35 billion terabytes. They recommend the use of deep stacking networks, a deep learning network in which each node is itself a neural network. The best feature of this design being the parallelisation of the calculations. For commercial big data processing, deep stacking networks seem to be the most sensible option for real time processing. For this task, GPU hardware is highly effective as of the present day so specialised hardware for deep learning would push the envelope further.

Taking all other factors into consideration, the results produced by deep learning result in an assessment as it being state of the art in computer vision, speech recognition and text understanding (Q. Zhang et al., 2018). Medical technology has shown better than human performance in tumour contouring (Lustberg et al., 2018) and bone-age estimation (Spampinato et al., 2017). No articles I’ve seen have reported lower rates of success than over average human levels, though some studies report only a competitive level (Zhao et al., 2018), that does not exceed the ability of alternate software or human ability. This gives the conclusion that it is important to acknowledge deep learning is not always the ideal solution to every problem.

Medical technology seems to be a less publicly advertised landscape for deep learning than is commonly known, with much focus of the public eye on automotive applications. Yet every indication in the body of the literature is that medical image processing is the preeminent field of study in deep learning applications. The future potential in medical tech is in two broad scopes; an increase in accuracy of diagnosis and treatment and a reduction in labour required by medical doctors. The first is accomplished through deep learning techniques that act as computational algorithms with greatly superior accuracy compared to current medical technology, the second through deep learning acting as a highly technical automation of current technology. Less time spent by doctors performing routine manual work should not be underrated due to the high demand on their labour in performing life and death operations, any increase in the ability to diagnose or treat patients means quite literally saving lives.

Self-driving cars are an area that has much documentation and work performed, though it seems the hype is far greater than the reality. Image processing for automobiles has seen brilliant steps forward over the past few years but it still faces challenges such as requiring a strong locally run CPU and GPU. Attempts have been made at running a cloud-based image processor though connection issues to the cloud server would be an issue. As human lives would be on the line it is reasonable to expect that such computing power would have to be local to the automobile itself, leading to a greater fusion of computing technology with automotive. With all that said, it seems inevitable that self-driving cars will be on the roads en masse within a matter of years, depending on the results of current road-testing being performed in the USA. Image recognition is vitally linked to this, with image quality and noise reduction being of critical importance. I conclude that there is no indication there is any barrier to self-driving cars being viable in the long term with only the highly complex image processing and associated navigation around perceived obstacles being the significant technical challenge.

My final conclusion is that the specialised field of deep learning has considerable overlap in much of the research with a few individuals. Geoffrey Hinton, a coinventor of Boltzmann machines, and Yoshua Bengio, both experts in the field, feature across several articles referenced in a range of publications, including together in Nature (LeCun, Bengio and Hinton, 2015).

# 5. Recommendations and Predictions

An expansion in the use of deep learning is inevitable as the technology matures, it is also a field that will be rapid in its expansion over the next few years, a trend noted by Litjens et al. (2017). Growth has been particularly strong since 2016. There has been swaying from unsupervised learning to supervised and now back to unsupervised learning, an observation noted in the journal, Nature (LeCun, Bengio and Hinton, 2015) and supported additionally by Litjens et al. (2017). I predict an increase in unsupervised learning applications accordingly, though it seems almost predestined for a swing back to supervised learning after another 5 years.

Image processing appears to be a central field for convolutional neural networks (CNN) with LeCun, Bengio and Hinton (2015) and LitJens et al. both stating the suitability of the architecture. I would go further and say that image processing is possibly over-saturated in research, with most of the studies focussed on image processing finding the same conclusions about CNNs. LeCun, Bengio and Hinton (2015) extend upon the CNN architecture in their advocacy for reinforcement learning, to better optimise classification tasks. However, given the wealth of research that I have studied in 2016 onwards that has taken place after the Nature article, where the bulk of deep learning articles exist, I disagree that reinforcement learning will be expanded at the rate the authors state. In any case it is stated that the technology of reinforcement learning to be in its infancy so if it is to emerge I would estimate a wider use cropping up in the 2020’s. Hinton is a highly influential source on deep learning with his original article (Hinton, 2006) who is highly cited so it would be unfair to entirely dismiss his input. Yet I cannot help but notice a lack of mention of reinforcement learning, further research into the subject is needed.

The automation of medical technology will be utterly dominated by advances in deep learning, making vast strides in the current day with the technological lag catching up at least a decade later. I foresee the challenges of implementation of deep learning in scanning applications to be less so about the practical ability for the technology to perform better than the average human doctor and more about the legal and ethical challenges of trusting computerised systems with identification of tumours and other anomalies. Supervision by a human doctor over this automatic process with the duty of manually performing a scan evaluation for cases of doubt is the most likely outcome. The technology will not be a case of replacement but of broader assistive technologies to widen a doctor’s productivity and accuracy. A common feature of almost all medical technology applications mentioned is their application towards diagnosis, other futuristic techniques such as robotic surgeons are more predicated on the maturity of other technologies like computer vision.

Gaps in medical research include bone and retinal image processing. A publicly available, labelled training set of medical scans from different fields would greatly help further development, an opinion espoused by Litjens et al. (2017). It is also an issue experienced with Mohsen et al. (2018), who obtained their dataset from the public domain. There is also a gap in space science applications, with far fewer papers compared to medical or automotive applications.

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