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. 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, 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.

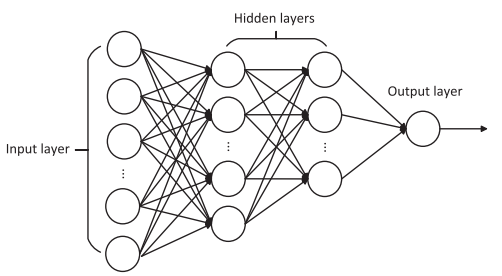


Fig 1 – Example Structure of a Neural Network, image taken from Xiao et al. (2018)

## 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 additional key words of “medical”, “scientific”, “commercial”, “industrial” and “applications”. An initial selection process involved picking articles and conference proceedings based on their relevance to deep learning. I then went into each article and downloaded a PDF copy where available and any associated articles I could find that were presented on the website. 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 without appreciable quality control yielded 93 articles of interest about deep learning. All articles gathered mention deep learning within the title or the abstract. Approximately 30 articles were carefully picked out one by one in a manual fashion with an eye for quality. The remainder 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 have had a basic skim read to confirm their utility. 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.

A deep learning approach called deep filtering using real Laser Interferometer Gravitational-Wave Observatory (LIGO) data has been performed to help identify gravitational waves (George and Huerta, 2018). Initially using simulated data, the authors had previously published an article on their simulated data findings, with real LIGO data used in this example. 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 is 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 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.

Segmentation of brain tumours in scans have been automated with deep learning (Zhao et al., 2018).

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%).

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.

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).

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.

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 also plays a significant role in data mining using big data (Zhang et al., 2018). Zhang et al. note that deep learning is used to learn features on extremely large datasets but that in the future with increases in computational power slowing down and a simultaneous increase in the size of data sets, it will be more difficult computationally.

Recommending items to a user of a service 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 performance more than twice as well as the slowest baseline model.

## 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 (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.

# 4. Conclusions

The predominant theme of deep learning is that it greatly reduces time spent performing tasks. This is multifaceted, through a direct reduction in computational time and a reduction in dimensionality of the data. Multiple studies (cite here) reference the potential of tackling the curse of dimensionality, a major factor that works against the use of very large datasets. The study on deep filtering for LIGO (George and Huerta, 2018) is 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 study on big data (cite here) is considered, it has a prescient statement that the contraction of Moore’s law means that the expansion of algorithms that reduce computational power by deep learning will likely become a necessary staple of projects that involve large datasets. 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 at 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, 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.

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.

# 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). 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).

Image processing appears to be a central field for convolutional neural networks with LeCun, Bengio and Hinton (2015) and LitJens et al. both stating the suitability of the architecture. LeCun, Bengio and Hinton (2015) extend upon the 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.

Gaps in medical research include bone and retinal image processing in deep learning and 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).

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