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DEEP LEARNING APPLICATIONS IN ENGINEERING: A SYSTEMATIC REVIEW.

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ABSTRACT. Recent advances in deep learning algorithms and computing have resulted in tremendous gains in deep learning capabilities. Deep learning is currently able to achieve near-human level performance on a number of tasks. As a result, deep learning has been deployed in various real-life applications. There exists a growing body of literature devoted to further advancement of deep learning software and hardware implementations. In this paper, we conduct a systematic review of deep learning applications with emphasis on relevant applications in engineering. We highlight their strengths and recommend remedies regarding their weaknesses.

1. INTRODUCTION

Deep learning is a subset of machine learning which is based on the structure of a neural network. Recent improvements in the efficiency and the architecture of the deep learning models as well as increased computational capacity have led to vast improvements in the performance of the deep learning models. In some tasks, deep learning models have achieved human level accuracy. It is not a stretch to imagine that at the current rate of progress deep learning will reach a point of human level accuracy on a large number of tasks. As a result, deep learning has been increasingly deployed in various applications. In this paper, we conduct a review of the existing use cases of deep learning models. We provide a taxonomy of the applications and describe the existing achievements in each field.

There exists several deep learning architectures including fully connected neural networks, convolutional neural networks, recurrent neural networks, reinforcement learning, and others. New deep learning architectures are continuously developed and the existing ones are being enhanced. In addition, the optimization techniques for locating the minimum values of the neural network loss functions are continuously being improved. Thus, the advances on the theoretical front have greatly contributed to the improved performance of deep learning models.

Another major catalyst of deep learning models has a tremendous improvement in computing power. Ever more powerful graphics processing units (GPUs) are designed

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and produced every year by the likes of Nvidia. Parallel computing and cloud computing have also allowed for increased computing capacity. Collaboration between AI labs and the giants in the tech sector led to more funding and increased availability of the resources to train larger models. The state-of-the-art models are trained on vast troves of data scraped from the internet that would not have been possible without the modern computing capacity.

2. Deep learning models

Deep learning models have made tremendous advances over the last decade which has led to their widespread adoption in various applications including medicine, education, network security, finance, engineering and others. There are several types of neural networks, each with its own unique characteristics and applications. Some of the most common types of neural networks include multilayer perceptron, convolutional neural networks, recurrent neural networks, and others. A hierarchy of common deep learning models is presented in Figure 1.

Feed-forward neural networks (FFNN) are the most basic type of neural network. They are the first type of neural network that was proposed in the form of a perceptron whose origins date back to 1940s. FFNN consist of an input layer, one or more hidden layers, and an output layer. The input is passed through the layers, and the output is produced at the end. It is also known as Multi-layer Perceptron (MLP) [9, 13]. MLP provides the prototypical architecture for deep learning models and serves as the base model for all other deep learning architectures.

Another common architecture is Recurrent Neural Networks (RNNs) which is designed to process sequential data, such as speech or time series data. They have a feedback connection, allowing the network to maintain an internal memory of previous inputs, which enables them to better handle sequential data [40]. In RNNs, the output in the current time step depends on the input in the current time step together with the output from the previous time step. Long Short-Term Memory (LSTM) networks: These are a type of RNN that can better handle the long-term dependencies in sequential data by introducing a memory cell, input gate, output gate, and forget gate [53]. LSTM were designed to help ameliorate the issue of exploding gradients that is often present in long RNNs. A powerful image processing model is Convolutional Neural Networks (CNNs) which is designed to process data with a grid-like topology, such as an image. They consist of multiple layers that learn to extract features from the input image, starting with simple features such as edges and lines, and progressing to more complex features such as shapes and objects [5]. The use CNN was extended beyond image processing applications to other fields.

Generative models have become prominent over the last half-decade. Autoencoder is one of the commonly used generative models [4, 56]. It is an unsupervised deep learning technique that learns to encode and decode the input data. Autoencoders are commonly used for dimensionality reduction, anomaly detection, data generation, and feature learning. Another common type of generative model is Generative Adversarial Networks (GANs) which consist of two parts [10]. First, a generator network that produces new data. Second, a discriminator network that tries to distinguish the generated data from the real data. GANs are commonly used for image synthesis, image translation and other generative tasks. Transformer is yet another commonly employed generative model. It is a neural network architecture that was introduced in the field of natural language processing (NLP) [44, 50]. It uses attention mechanisms to focus on important parts of the input and can handle input sequences of variable length.

More recently Graph Neural Networks (GNNs) have gained popularity [8, 52]. These networks are designed to process graph-structured data, such as social networks or molecular structures. They can learn to extract features from the graph and make predictions about the graph structure. Each type of neural network has its own strengths and weaknesses, and the choice of the network architecture depends on the problem at hand, the available data and computational resources. While in some cases the choice of the model might be clear, in other cases multiple models may provide similar results.

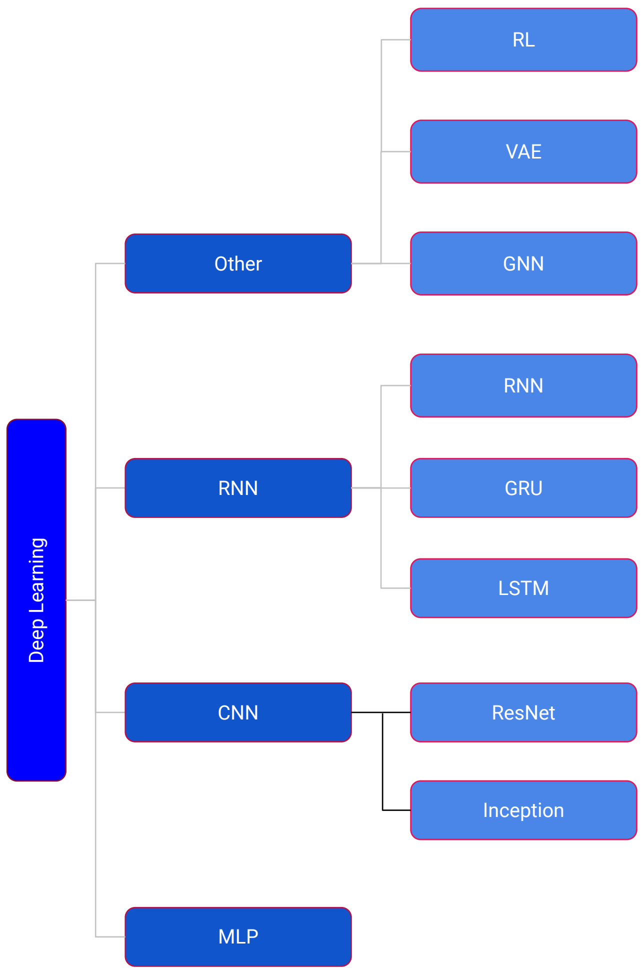

FIGURE 1. Hierarchy of common deep learning models.

3. APPLICATIONS OF DEEP LEARNING

The performance of deep learning models has promoted their use in various applications [32, 57]. In some cases, the accuracy of the deep leaning models can reach near human levels. The success of deep learning depends as much on the algorithms and computing power as the availability of large troves of data for training. Since the explosion in data collection and data storage, the amount of training data available for deep learning models has vastly increased which, in turn, has led to better models.

Deep learning model in engineering can be grouped into four major categories according to the the applications: computer vision, speech and text recognition, manufacturing, and transportation as shown in Figure 2.

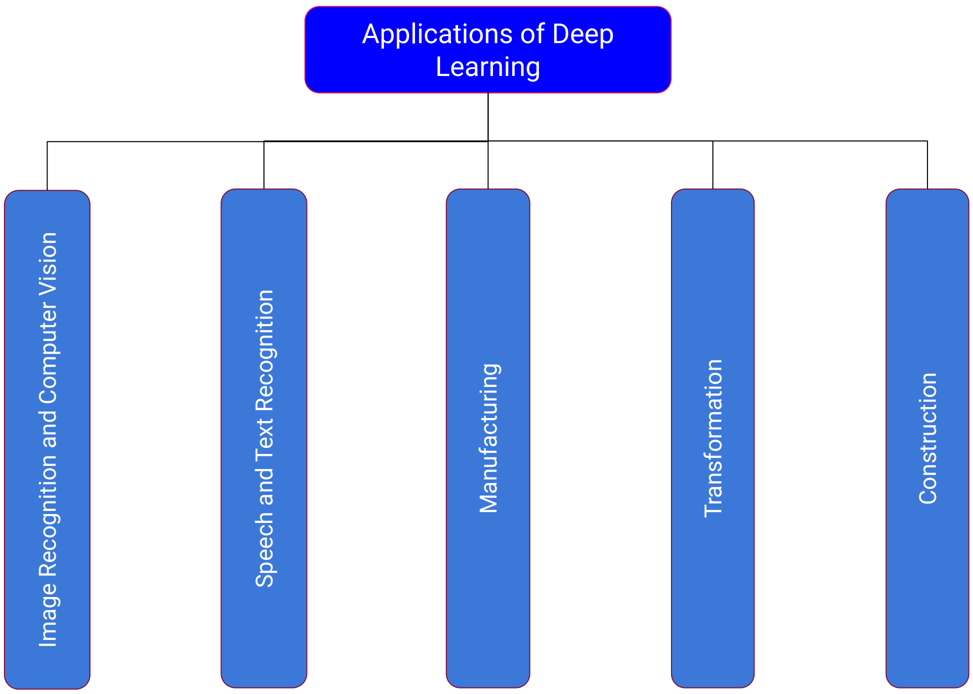

FIGURE 2. Deep learning applications.

3.1. **Image Recognition and Computer Vision.** Deep learning, particularly CNNs, has been widely used in image recognition and computer vision [7]. CNNs are a type of neural network that are designed to process data with a grid-like topology, such as an image. They consist of multiple layers that learn to extract features from the input image, starting with simple features such as edges and lines, and progressing to more complex features such as shapes and objects. The main component of a CNN is the convolution window which is moved around the input image in order to learn new features.

One of the most popular applications of CNNs in image recognition is object detection [51]. Object detection is the task of identifying and locating objects within an image or video. The initial progress in object detection within an image prompted its extension to videos. CNNs have also been used to train models that can detect objects such as vehicles, individuals, and traffic signs in real-time, which is crucial for applications such as autonomous vehicles and surveillance systems.

Another popular application of CNNs in computer vision is image segmentation [36]. Image segmentation is the task of dividing an image into multiple segments, or regions, each of which corresponds to a specific object or background. CNNs have been used to train models that can segment images into different classes, such as foreground and background, or different objects, such as cars, pedestrians, and road signs.

CNNs have also been used in image classification [48]. Image classification is the task of assigning a label or class to an image based on its content. CNNs have been used to train models that can classify images into different classes such as animals, vehicles, and natural scenes with high accuracy. In particular, CNNs have performed extremely well on image recognition tasks such as ImageNet achieving over 90% accuracy level.

Furthermore, CNNs have been used in other computer vision tasks such as image captioning, where the model is trained to generate a natural language description of an image, and visual question answering, where the model is trained to answer questions about an image [43].

One of the advantages of using deep learning in image recognition and computer vision is that it can learn to extract features from images automatically, without the need for manual feature engineering [34]. Automatic feature learning allows for autonomous processing of computer models. This enables the model to learn more complex and abstract features that are not easily identified by human experts. Additionally, deep learning models can be trained on large amounts of data, which enables them to improve their performance over time.

3.2. **Speech and Text Recognition.** Deep learning has been widely utilized in speech and text recognition. Speech recognition is the task of converting spoken language into text, and text recognition is the task of converting text in images or videos into machine-readable text. RNNs and LSTM networks are among the most common deep learning architectures used in speech recognition [30]. As mentioned above, RNNs are neural networks that can process sequential data, such as speech, by maintaining an internal memory of previous inputs. LSTMs are a type of RNN that can better handle the long-term dependencies in speech data by introducing a memory cell, input gate, output gate and forget gate whose aim is to combat the issue of diminishing (vanishing) gradient.

These architectures have been used to train models that can transcribe speech with high accuracy. These models can be used in various applications such as voice commands, voice-controlled devices, and call routing in telecommunications [46]. In text recognition, CNNs have been widely used to recognize text in images and videos. CNNs can learn to recognize patterns in images, and they have been used to train models that can recognize text in images, even when the text is distorted, skewed or has different fonts. These models can be used in various applications such as license plate recognition, handwriting recognition, and optical character recognition [42].

In addition, deep learning models have been used in other text-related tasks such as natural language processing (NLP). NLP is the task of analyzing, understanding and generating human language [41]. These models can be used in various applications such as language translation, text summarization, and sentiment analysis. One of the advantages of using deep learning in speech and text recognition is that it can learn to recognize patterns in speech and text data automatically, without the need for manual feature engineering. Additionally, deep learning models can be trained on large amounts of data, which enables them to improve their performance over time.

3.3. **Manufacturing.** Deep learning has been widely used in manufacturing for various applications such as quality control, anomaly detection, predictive maintenance, and others [31]. One of the key applications of deep learning in manufacturing is in quality control. In this field, deep learning models, specifically CNNs, have been used to inspect and classify products, which is significant for protecting the quality of the manufactured goods. These models can be trained to detect defects in products, such as cracks or missing parts, and to classify products into different categories, such as good or defective. Deep learning allows for a more efficient and accurate quality control process, reducing the number of defective products, and increasing production efficiency [6].

Anomaly detection is another application of deep learning in manufacturing [1]. Deep learning models, including autoencoders and variational autoencoders, have been used to detect abnormal patterns in sensor data from manufacturing equipment. The models are trained to detect patterns that deviate from the normal operating conditions of the equipment, pointing to an anomaly or a potential failure. It enables for early detection of equipment failures, reducing downtime and increasing the overall efficiency of the manufacturing process.

Finally, deep learning has also been used in predictive maintenance, where deep learning models including RNNs and LSTM networks, have been used to predict the remaining useful life of equipment or predict when maintenance is needed. These models can be trained on sensor data from manufacturing equipment and can predict when a failure is likely to occur, allowing for scheduled maintenance, reducing downtime and increasing the overall efficiency of the manufacturing process.

3.4. **Transportation.** Deep learning has been used in transportation in several applications including autonomous vehicles, traffic management, and predictive maintenance [47]. One of the most important applications of deep learning in transportation is in autonomous vehicles, where deep learning models such as CNNs and object detection algorithms, have been used to enable vehicles to perceive and understand the environment. The models are trained to identify and classify objects such as other vehicles, pedestrians, and traffic signs, which is crucial for safe navigation. In addition, deep learning models have been used to predict the motion of other objects in the environment including vehicles and pedestrians, which is significant for planning safe and efficient trajectories for autonomous vehicles [38].

Another application of deep learning in transportation is in traffic management, where deep learning models including RNNs and LSTMs have been used to analyze traffic data [2]. It is particularly useful for processing traffic flow and congestion, in order to optimize traffic management strategies. These models can be trained for traffic pattern prediction and bottlenecks identification, which in turn can be used to optimize traffic signal timings and reroute traffic to reduce congestion.

Deep learning models have also been used in predictive maintenance for transportation [39]. Concretely, deep learning models have been used to predict the remaining useful life of transportation equipment, such as vehicles and aircraft, or predict when maintenance is needed. These models can be trained on sensor data from the transportation equipment, and utilized for prediction of the time when a failure is likely to occur, allowing for scheduled maintenance, reducing downtime, and increasing the overall efficiency of the transportation system.

In summary, deep learning has been widely used in transportation for various applications such as autonomous vehicles, traffic management, and predictive maintenance. Its ability to learn from large amounts of data and improve its performance over time makes it a powerful tool for transportation engineers and system operators to solve complex problems and improve the efficiency of transportation systems.

3.5. **Construction.** Construction is one of the growing applications of deep learning including construction site monitoring, building information modeling (BIM), automated construction, and quality control [3]. One of the key use cases of deep learning in construction is in construction site monitoring. Deep learning models are used to analyze images and videos from construction sites to monitor the progress of construction projects. The models are able to detect and track construction equipment, workers, and materials on the site, providing real-time information on the progress of the project. It ensures a more efficient construction site management and enables early detection of potential delays or problems.

Another increasingly popular application of deep learning in construction is in building information modeling (BIM) [49]. Deep learning models including NLP algorithms and graph neural networks, have been used to extract information from building design and construction documents. These models can be trained to understand the structure and meaning of the documents, allowing for efficient data extraction and management. This enables better collaboration and coordination among the different stakeholders in the construction process, such as architects, engineers, and contractors, and improves the overall quality of the building.

Deep learning has been often used in automated construction, such as robotic vision algorithms, to enable robots to understand and interact with the construction environment. These models can be trained to recognize and manipulate objects in the environment, allowing for the automation of certain construction tasks such as brick laying, masonry, and welding [33]. Furthermore, deep learning models have been applied to the quality control process, inspecting and classifying products including concrete, steel and other construction materials, to safeguard the quality of the manufactured goods.

3.6. **Forecasting and other applications.** Deep learning has also been widely used in many fields outside of engineering including medicine, finance, translation, astronomy, education, and others [18, 19, 21, 22, 24, 26, 27]. In particular, deep learning forecasting models such as LSTM have been popular in various contexts. In finance, time series deep learning models based on RNN, LSTM, and LSTM-CNN models have gained a significant traction. These models are deployed to forecast the value of stocks, foreign exchange rates, cryptos, and other financial assets [11, 12, 14, 23, 25, 28, 29]. Recently, in medicine, deep learning models have been widely utilized to forecast Covid-19 cases. LSTM, GNN, and other highly advanced models have been deployed to help manage the global pandemic. The state of the art models have been able to achieve significant accuracy and provide important help in handling the pandemic

[16, 20, 37, 54, 55]. Forecasting in meteorology using deep learning has also been actively explored. Deep learning models are able to replace complicated weather models and produce comparatively accurate forecast in temperature, rain fall, and other weather indicators.

4. Conclusion

Deep learning has recently taken the society by storm. The advent of successful natural language processing models has highlighted the potential of deep learning. In this paper, we discuss modern applications of deep learning with emphasis on engineering applications. Concretely, an overview of the existing research directions and the structure of the current state of applied deep learning is provided. Strengths and weaknesses of deep learning in each application is analyzed.

Deep learning has proved to be an effective tool in engineering, providing a more efficient and accurate process, reducing downtime and increasing production efficiency. However, as with any technology, deep learning also has its limitations, such as the need for large amounts of labeled data for training, and the lack of interpretability of the learned models. Despite these limitations, the advantages of deep learning in manufacturing far outweigh its limitations, and it is expected to play an increasingly important role in manufacturing in the future.

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