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Investigating and Advancing Approaches in Deep Learning Models: Platforms, Applications, and the Dynamics of Emerging Research Trends

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Abstract: ***Deep learning has rapidly emerged as a focal point, captivating both academic research and industrial applications in recent years. This paper provides a concise overview of the pivotal concepts and determinants underpinning the evolution of deep learning. The impact of data augmentation (DA) on deep learning shines through recent demonstrations, leading to heightened accuracy, stability, and mitigated overfitting. Operating within the broader sphere of machine learning, deep learning's prowess lies in its capacity to autonomously uncover intricate patterns and representations from raw data. Its evolution from conventional machine learning approaches has unlocked transformative potential, propelling advancements in areas such as image classification, speech synthesis, and medical diagnosis. However, challenges pertaining to interpretability, data scarcity, and model generalization persist, fostering an active field of research that continually refines deep learning techniques. The ramifications of this technology are profound, as it reshapes industries and fuels innovation, thereby shaping the trajectory of AI-driven solutions. In contrast, strides in image and spectral data analysis have harnessed the power of synthetic data facilitated by sophisticated forward models and generative unsupervised deep learning methods. This paper offers a comprehensive perspective on deep learning techniques, first introducing them at a high level and subsequently delving into their applications in atomistic simulation, materials imaging, spectral analysis, and natural language processing. Across these modalities, we explore theoretical and experimental data applications, prevalent modeling strategies with their strengths and limitations, as well as available software and datasets. The exposition encapsulates six principal deep learning models that dominate contemporary academic research, elucidating their principles and characteristics. Beyond academia, this work examines industrial applications, such as speech and image recognition, artificial intelligence, and anticipates forthcoming trends and challenges in these domains."***

Keywords: deep learning; neural networks; learning models; applications, Generative learning, Hybrid learning, Intelligent systems, Emergent Applications, Machine learning, Artificial Intelligence

1. Introduction

Today, intelligent systems that offer artificial intelligence capabilities often rely on machine learning. Machine learning describes the capacity of systems to learn from problem-specific training data to automate the process of analytical model building and solve associated tasks. Deep learning is a machine learning concept based on artificial neural networks. For many applications, deep learning models outperform shallow machine learning models and traditional data analysis approaches. In this paper, we summarize the fundamentals of machine learning and deep learning to generate a broader understanding of the methodical underpinning of current intelligent systems. In particular, we provide a conceptual distinction between relevant terms and concepts, explain the process of automated analytical model building through machine learning and deep learning, and discuss the challenges that arise when implementing such intelligent systems in the field of electronic markets and networked business. These naturally go beyond technological aspects and highlight issues in human-machine interaction and artificial intelligence servitization.

Deep learning, a cutting-edge subset of machine learning, has catalyzed in the field of artificial intelligence (AI). With roots in neural networks and inspired by the structure of the human brain, deep learning algorithms possess an extraordinary capability: the automatic extraction of intricate patterns and features from raw data. In contrast to traditional machine learning methods, deep learning models operate through multiple layers of interconnected neurons, also known as artificial neural networks. These layers allow the model to progressively learn and transform input data, enabling the system to identify complex hierarchies of information that would be challenging to capture using manual feature engineering. This attribute makes deep learning exceptionally well-suited for tasks such as image and speech recognition, natural language understanding, and even autonomous decision-making. The impact of deep learning is profound, transforming industries and fields across the spectrum. In the realm of computer vision, deep learning has revolutionized image classification, object detection, and facial recognition. Natural language processing has seen remarkable progress in machine translation, sentiment analysis, and chatbot systems. Moreover, deep learning has made significant contributions to healthcare through medical image analysis, disease prediction, and drug discovery.

Deep learning represents a transformative force in the AI landscape, combining intricate neural network architectures with the abundance of data and computational power. As researchers continue to refine algorithms, address challenges, and unlock novel applications, the trajectory of deep learning promises to shape the future of AI, ushering in an era of unprecedented capabilities and opportunities.

Computing-based Big Computin, and the Internet of Things (IoT)/Cyber-Physical Systems (CPS), the topic of Deep

Learning has come to dominate industry and research spheres for the development of a variety of smart-world systems, and for good reason. Deep learning has shown significant potential in approximating and reducing large, complex datasets into highly accurate predictive and transformational output, greatly facilitating human-centered smart systems. In contrast to complex hard-coded programs developed for a sole inflexible task, deep learning architectures can be applied to all types of data, be they visual, audio, numerical, text, or some combination. In addition, advanced deep learning platforms are becoming ever more sophisticated, often open source and available for widespread use. Furthermore, major companies, including Google, Microsoft, Amazon, Apple, etc., are heavily Corresponding Author: Prof. Wei Yu (Email: wyu@towson.edu). investing in deep learning technologies to supply hardware and software innovations that can further improve deep learning performance, which can be used for next generation smartworld products.

Though regression analysis and auto-encoding are not new topics in the field of machine learning, deep learning implementations can provide higher accuracy and better predictive performance, and are more flexible and configurable. As one of the largest areas of deep learning applications, supervised learning tasks for classification have far outstripped even human abilities in areas like handwriting and image recognition. In addition, unsupervised learning on datasets without any particular labels has shown the potential for the extraction of unforeseen analytical and commercial value in the form of clustering and statistical analysis. Potentially the most interesting yet, reinforcement learning provides the potential for deep learning without human supervision, through feedback from a connected environment. This type of deep learning has been heavily applied to the field of robotics and computer vision [36].

In recent years, promising deep learning based interatomic potential energy surface (PES) models have been proposed that can potentially allow us to perform molecular dynamics simulations for large scale systems with quantum accuracy. However, making these models truly reliable and practically useful is still a very non-trivial task. A key component in this task is the generation of datasets used in model training. In this paper, we explain the Deep Potential GENerator (DP-GEN), an open-source software platform that implements the recently proposed" on-the-fly" learning procedure (Zhang et al. 2019) and is capable of generating uniformly accurate deep learning-based PES models in a way that minimizes human intervention and the computational cost for data generation and model training.

DP-GEN automatically and iteratively performs three steps: exploration, labeling, and training. It supports various popular packages for these three steps: LAMMPS for exploration, Quantum Espresso, VASP, CP2K, etc. for labeling, and DeePMD-kit for training. It also allows automatic job submission and result collection on different types of machines, such as high-performance clusters and cloud machines, and is adaptive to different job management tools, including Slurm, PBS, and LSF. As a concrete example, we illustrate the details of the process for generating a general-purpose PES model for Cu using DP-GEN.

2. Representations of Process

The Challenge of Representation One of the most formidable hurdles in AI research is enabling computers to grasp and inherently break down structural representations of problems, akin to human cognition. Certain problems lend themselves to simpler representation through recipes, where explicit instructions guide the computer's actions. Such instructions involve predefined logical steps to tackle specific problems or problem sets.

For instance, we can program a computer to navigate a satellite into space. However, the endeavor becomes markedly intricate when attempting to imbue a computer with empathy, love, or even more elemental abilities like composing poetry or comprehending spoken language. It's essential to note that translation and interpretation are distinct realms; the latter necessitates a profound grasp of linguistic structures. While translation poses its challenges, comprehension introduces an entirely different puzzle.

In theoretical computer science, there exists a classification of problems into two categories: tractable (P) and intractable (NP) problems. Without delving into technical nuances, intractable (NP) problems are those that cannot be fully resolved by a computer following a set of instructions, regardless of the time allocated.

When discussing problem representation, we allude to the category of problems that resist easy formulation a category encompassing intractable problems. In essence, these are problems that prove elusive to encapsulate or cannot be articulated as a sequence of logical directives. These are the challenges that form the crucible of deep learning's ambitions to tackle the seemingly insurmountable.

Deep learning operates through intricate neural network architectures, enabling computers to automatically learn intricate patterns and representations from data. This process involves several key steps:

We now listed a categorical review of deep learning architectures by learning mechanism and learning output task, and provide brief descriptions of the many algorithmic implementations of each. The primary learning mechanisms are supervised learning, unsupervised learning, and reinforcement learning. In general, learning mechanisms are classified by the type of input data that they operate upon. Output tasks include classification, regression, dimensionality reduction, clustering, and density estimation.

1) **Data Collection and Preparation:** Deep learning models require a significant amount of labeled data for training. The data is divided into training, validation, and testing sets. Proper data preprocessing, such as normalization and transformation, is performed to make the data suitable for model training.
2) **Neural Network Architecture:** A deep learning model consists of interconnected layers of artificial neurons. Each layer performs a specific type of transformation on the input data. The input layer receives raw data, hidden

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layers process intermediate representations, and the output layer produces predictions or classifications.

3) **Weight Initialization:** The connections (weights) between neurons are initialized with small random values. These weights are crucial as they determine the strength of connections and influence the network's learning process.
4) **Forward Propagation:** During training, data is fed through the network in a process called forward propagation. Each neuron calculates a weighted sum of its inputs, applies an activation function to produce an output, which becomes the input for the next layer.
5) **Loss Calculation:** The output of the neural network is compared to the actual target values using a loss function (also known as a cost or objective function). The loss function quantifies the difference between predictions and actual values.
6) **Backpropagation:** The network's performance is evaluated using the loss value. Backpropagation involves calculating the gradient of the loss with respect to the weights. This gradient guide the optimization algorithm to adjust the weights in a way that reduces the loss, effectively updating the network's parameters.
7) **Optimization:** Various optimization algorithms, such as stochastic gradient descent (SGD) and its variants, are employed to update the weights iteratively. These algorithms adjust the weights in the direction that reduces the loss function.
8) **Training and Validation:** The model is trained iteratively on the training dataset. During training, the model's performance on the validation dataset is monitored to prevent overfitting (where the model performs well on training data but poorly on new data).
9) **Hyperparameter Tuning:** Parameters such as learning rate, batch size, and the number of layers are considered hyperparameters. Optimizing these hyperparameters ensures efficient model training and better performance.
10) **Testing and Evaluation:** Once the model is trained, it's tested on a separate testing dataset to assess its performance on unseen data. Metrics like accuracy, precision, recall, and F1-score are used to evaluate the model's effectiveness.
11) **Inference:** After training, the model is deployed for inference, where it makes predictions on new, unseen data. The input data undergoes the same preprocessing and forward propagation steps, producing output predictions.

In the first decade of the twenty-first century, researchers have mainly discussed the shallow artifcial neural network (ANN) based on optimization algorithms for certain aspects, but the complexity of neural networks has not been extended too much. Till the 2012 ImageNet competition, Hiton and other scholars applied a DL method named AlexNet (a variant of convolutional neural network (CNN)), which greatly improved the predictive accuracy, giving rise to the wide spreading of DL algorithms in numerous felds and disciplines. A systematic review of DL development timeline as shown in Fig. 2. It can be seen that DL gets great process in recent decades. As one of the cutting-edge algorithms in AI, DL is advanced in defning complex nonlinear relationship between features in different domains, such as, health and medicine (Lisboa 2002), business and management (Wong et al. 1997), natural language processing(NLP) (Mikolov et al. 2010), image processing (Ayyıldız and Çetinkaya 2017; Egmont-Petersen et al. 2002; He et al. 2015), geosciences and remote sensing (Lary et al. 2016), mathematics (Gao et al. 2019a, b, 2018a, b), civil engineering (Gandomi and Alavi 2012a, b; Lazarevska et al. 2014; Zhang et al. 2020c, 2014), early warnings related to geotechnical problems(Ch ou and Thedja 2016), risk assessment (Adams and Kanaroglou 2016; Dong et al. 2017).

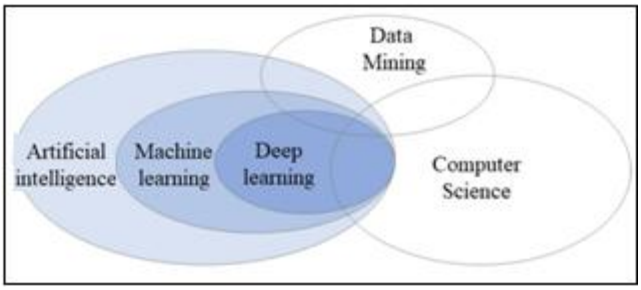

Figure 1: Venn diagram representing the relationships between AI, ML and DL

3. Literature Survey

Deep learning (DL), a branch of machine learning (ML) and artificial intelligence (AI) is nowadays considered as a core technology of today's Fourth Industrial Revolution (4IR or Industry 4.0). Due to its learning capabilities from data, DL technology originated from artifcial neural network (ANN), has become a hot topic in the context of computing, and is widely applied in various application areas like healthcare, visual recognition, text analytics, cybersecurity, and many more. However, building an appropriate DL model is a challenging task, due to the dynamic nature and variations in real-world problems and data. Moreover, the lack of core understanding turns DL methods into black-box machines that hamper development at the standard level.

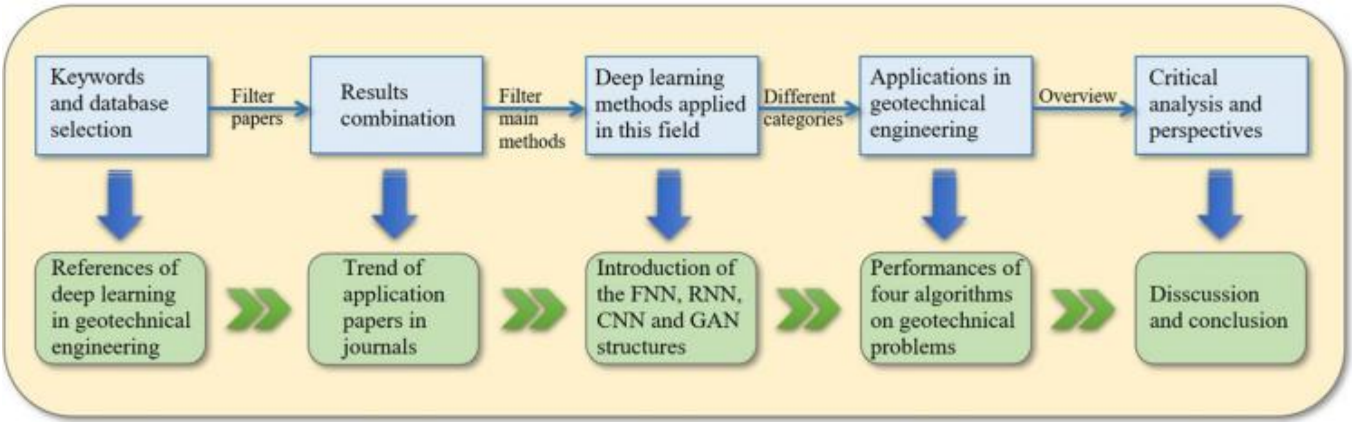

Figure 2: Research frame of DL review in geotechnical engineering

Machine learning incorporates a vast array of algorithmic implementations, not all of which can be classified as deep learning. For example, singular algorithms, including statistical mechanisms like Bayesian algorithms, function approximation such as linear and logistic regression, or decision trees, while powerful, are limited in their application and ability to learn massively complex data representations. Deep learning has developed from cognitive and information theories, seeking to imitate the learning process of human neurons and create complex interconnected neuronal structures. As one of the key concepts of computing neurons and the neural model, the ability for a generic neuron to be applied to any type of data and learn indiscriminately is a powerful concept [1]. In essence, there is no singular structure for each application, but instead a generally applicable model for all applications.

With the advancement of computing technologies, the implementation of large collections of neurons was possible, giving rise to neural networks. Indeed, though neural networks are becoming commonplace, also they are, an old technology [2] that fell out of favor because of complexity and computing deficiencies. By definition of deep learning is the application of multineural, multi-layer neural networks to perform learning tasks, including regression, classification, clustering, auto-encoding, and others. Conceptually, the most basic computational neuron, the sigmoid neuron, can be considered as a single logistic node (though there are many other algorithms that can be implemented as activation functions). Each neuron is connected to the input ahead of it, and a loss function is used to update the weights of the neuron and optimize the logistic fit to the incoming data.

As part of a neural network layer, multiple parallel neurons initiated with different weights learn on the same input data simultaneously. In the application of multiple layers of multiple nodes, each node learns from all the outputs of the previous layers, stepwise reducing the approximation of the original input data to provide an output representation set. Thus, the complexity of multiple interconnected neurons is evident.

Broadly defined, AI comprises any technique that enables computers to mimic human behavior and reproduce or excel over human decision-making to solve complex tasks independently or with minimal human intervention (Russell and Norvig 2021). As such, it is concerned with a variety of central problems, including knowledge representation, reasoning, learning, planning, perception, and communication, and refers to a variety of tools and methods (e.g., case-based reasoning, rule-based systems, genetic algorithms, fuzzy models, multi-agent systems) (Chen et al. 2008). Early AI research focused primarily on hard-coded statements in formal languages, which a computer can then automatically reason about based on logical inference rules.

This is also known as the knowledge base approach (Goodfellow et al. 2016). However, the paradigm faces several limitations as humans generally struggle to explicate all their tacit knowledge that is required to perform complex tasks (Brynjolfsson and McAfee 2017). Machine learning overcomes such limitations. Generally speaking, ML means that a computer program's performance improves with experience with respect to some class of tasks and performance measures (Jordan and Mitchell 2015). As such, it aims at automating the task of analytical model building to perform cognitive tasks like object detection or natural language translation. This is achieved by applying algorithms that iteratively learn from problem-specific training data, which allows computers to find hidden insights and complex patterns without explicitly being programmed (Bishop 2006). Especially in tasks related to high-dimensional data such as classification, regression, and clustering, ML shows good applicability. By learning from previous computations and extracting regularities from massive databases, it can help to produce reliable and repeatable decisions. For this reason, ML algorithms have been successfully applied in many areas, such as fraud detection, credit scoring, next-best offer analysis, speech and image recognition, or natural language processing (NLP).

Many researchers have taken steps in this field and have identified various techniques for increasing the data sample size and increasing the generalization of the neural network used. The authors in the [6] have discussed and compared the different augmentation techniques over AlexNet model of CNN architecture. The dataset used by the authors were ImageNet and CIFAR10. The authors have compared the performance of different augmentation techniques like Flipping, Rotation, Noise, Shifting, Cropping, PCA jittering GAN and WGAN. As per authors, only rotations and WGAN have shown better results than others. The survey was conducted by [7] for semantic segmentation of image and video using deep learning techniques. The authors have focused on the review of deep learning methods for semantic segmentation which are applied to various applications. Sematic segmentation in computer vision is one of the key problems in 2D images, videos, or even 3D images and volumetric data. The problem of semantic segmentation is very well defined by the authors and reviewed on various deep learning models using different datasets. An augmentation strategy with Perlin noise for image classification was presented by [3]. This augmentation is applied to pixel-by-pixel and different image patterns. They have used images of 106 patients. They have considered 100 regions of interest for each of class of image patterns were selected for deep learning classification.

The main problem faced by many researchers in the field of deep learning to maximize its generalization is the availability of large dataset. There are so many techniques used to increase the size of data set like image augmentation, dropout, transfer learning etc. In [4] the authors have presented new method called smart augmentation to increase the precision and to solve the problem of overfitting of the target network. The smart augmentation creates a network which automatically to generate the augmented data during training process thereby reducing network loss A method is proposed by [5] used generative adversarial network to train the synthetic MRI images with brain tumors. They have used two public data sets of brain MRI.

They have presented two benefits of using this synthetic data: 1) efficient performance of tumor segmentation by resisting the synthetic images as a form if image augmentation; 2) they have demonstrated the generative models as a anonymous based tool.

4. Deep Learning Model

A deep learning model is a computational architecture comprised of interconnected layers of artificial neurons, designed to learn and extract hierarchical patterns and representations from data. These models are a central component of deep learning, a subset of machine learning, and have demonstrated remarkable capabilities in solving complex problems across various domains, including image recognition, natural language processing, and more.

There are the various Deep learning model:

Supervised learning	Supervised learning requires a training dataset that covers examples for the input as well as labeled answers or target values for the output. An example could be the prediction of active users subscribed to a market platform in a month's time as output (considered as the target variable or y variable) based on different input characteristics, such as the number of sold products or positive user reviews (often referred to as input features or x variables). The pairs of input and output data in the training set are then used to calibrate the open parameters of the ML model. Once the model has been successfully trained, it can be used to predict the target variable y given new or unseen data points of the input features x. Regarding the type of supervised learning, we can further distinguish between regression problems, where a numeric value is predicted (e.g., number of users), and classification problems, where the prediction result is a categorical class affiliation such as "lookers" or "buyers"
Unsupervised learning	Unsupervised learning takes place when the learning system is supposed to detect patterns without any pre-existing labels or specifications. Thus, training data only consists of variables x with the goal of finding structural information of interest, such as groups of elements that share common properties (known as clustering) or data representations that are projected from a high-dimensional space into a lower one (known as dimensionality reduction) (Bishop 2006). A prominent example of unsupervised learning in electronic markets is applying clustering techniques to group customers or markets into segments for the purpose of a more target-group specific communication.
Reinforcement learning	In a reinforcement learning system, instead of providing input and output pairs, we describe the current state of the system, specify a goal, provide a list of allowable actions and their environmental constraints for their outcomes, and let the ML model experience the process of achieving the goal by itself using the principle of trial and error to maximize a reward. Reinforcement learning models have been applied with great success in closed world environments such as games (Silver et al. 2018), but they are also relevant for multi-agent systems such as electronic markets (Peters et al. 2013).

1) Supervised Models:

- **Classic Neural Networks (Multilayer Perceptrons):** These are the foundational deep learning models. They consist of input, hidden, and output layers of neurons. They're used for a wide range of tasks, from simple regression to more complex classification problems.
- **Convolutional Neural Networks (CNNs):** Designed for processing grid-like data like images and videos, CNNs use specialized convolutional layers to automatically detect spatial patterns.[9] They're highly effective in tasks like image recognition and object detection.

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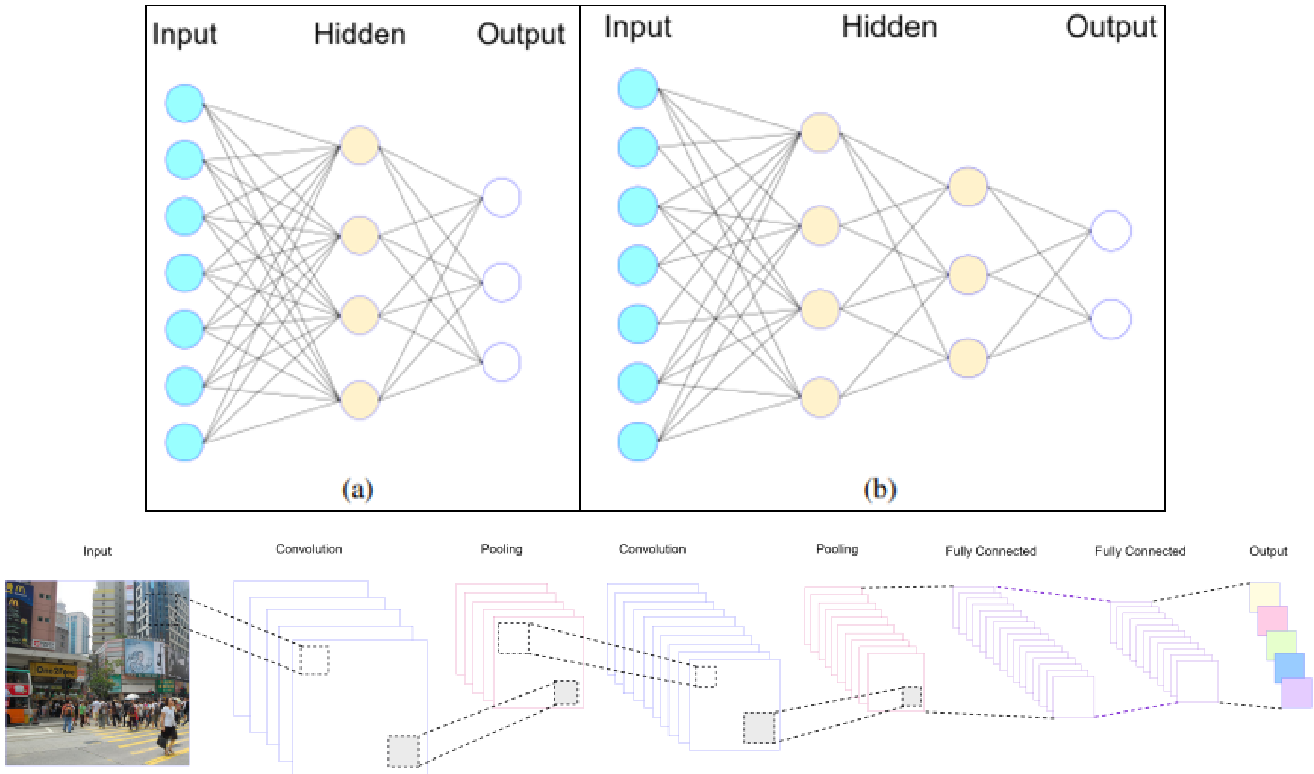

Figure 2: Structure of Neural network & CNN

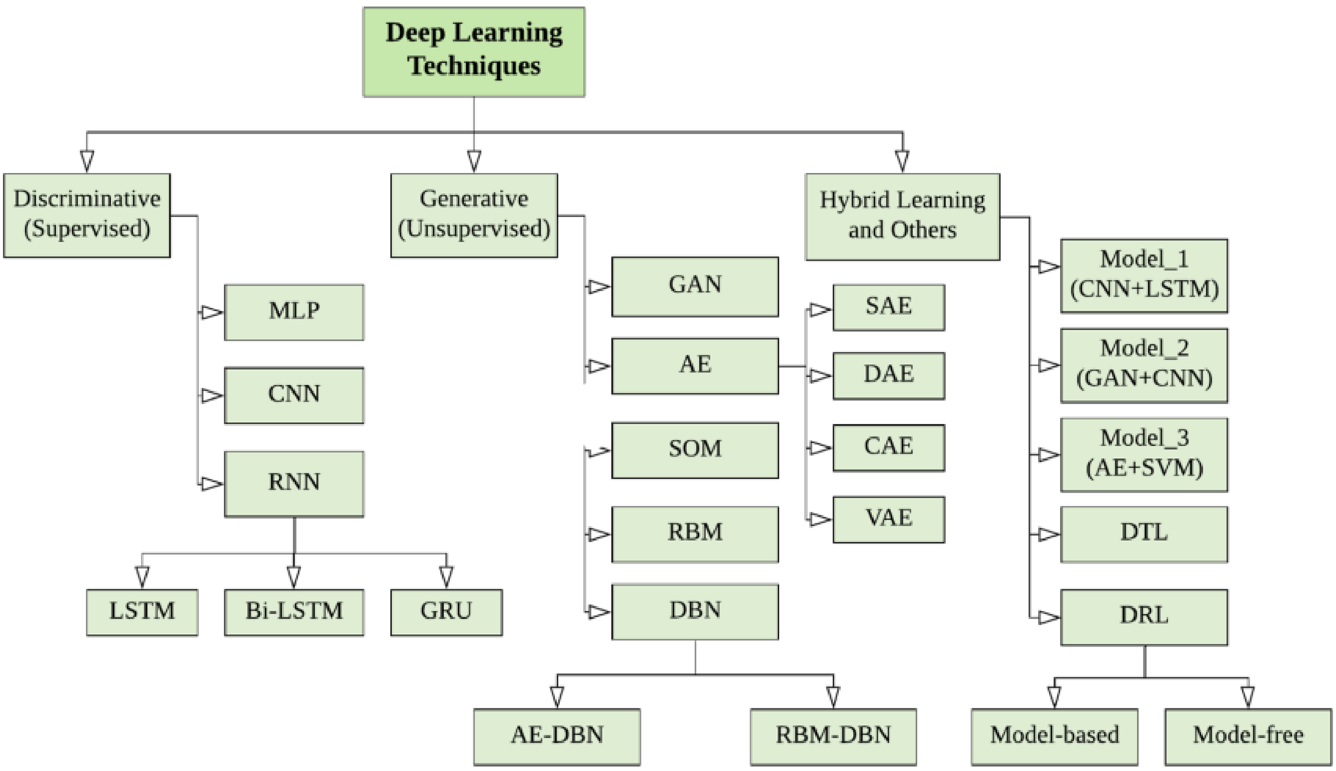

Figure 3: A taxonomy of DL techniques, broadly divided into three major categories (i) deep networks for supervised or discriminative learning, (ii) deep networks for unsupervised or generative learning, and (ii) deep networks for hybrid learning and relevant others

- **Recurrent Neural Networks (RNNs):** Tailored for sequential data, RNNs maintain a hidden state that captures context from previous steps. They're well-suited for tasks like natural language processing, speech recognition, and time-series analysis.

2) **Unsupervised Models:**

- **Self-Organizing Maps (SOMs):** SOMs are used for dimensionality reduction and visualization of high-dimensional data. They organize data points into a lower-dimensional grid while preserving their topological relationships.

- **Boltzmann Machines:** These models are a type of energy-based generative model that can capture complex probability distributions over input data. They have applications in various unsupervised learning tasks, including feature learning and data generation.
- **AutoEncoders:** Autoencoders consist of an encoder and a decoder network. They're used for feature learning, dimensionality reduction, and denoising. The encoder compresses input data into a lower-dimensional representation, and the decoder reconstructs the original data from this representation.

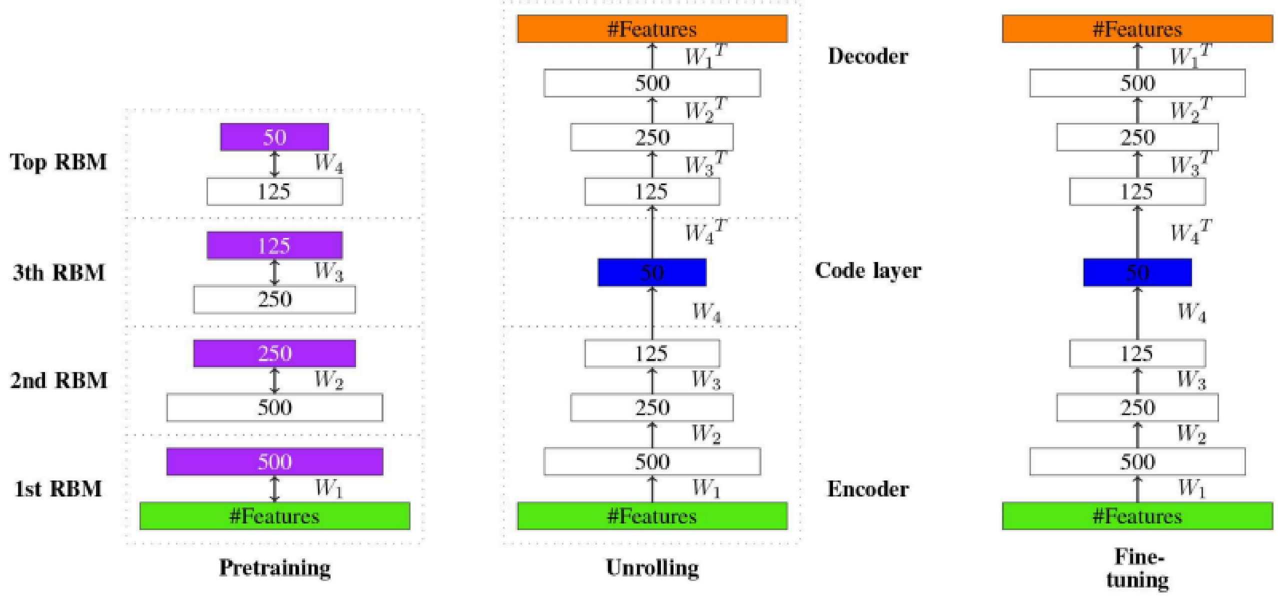

Figure 4: Visualizing the idea of autoencoder learning. The learned new encoding of the input is represented in the code layer (shown in blue).

In Fig [4] , an illustration of the learning process is shown. Here, the coding layer corresponds to the new encoding c providing, e.g., a reduced dimension of x. An Autoencoder does not utilize labels and, hence, it is an unsupervised learning model. In applications, the model has been successfully used for dimensionality reduction. Autoencoders can achieve a much better two-dimensional representation of array data, when an adequate amount of data is available (Hinton and Salakhutdinov, 2006). Importantly, PCAs implement a linear transformation, whereas Autoencoders are non-linear. Usually, this results in a better performance. We would like to highlight that there are many extensions of these models, e.g., sparse autoencoder, denoising autoencoder or variational autoencoder (Vincent et al., 2010; Deng et al., 2013; Pu et al., 2016).

Long short-term memory networks: Long short-term memory (LSTM) networks were introduced by Hochreiter and Schmidhuber in 1997 (Hochreiter and Schmidhuber, 1997). LSTM is a variant of a RNN that has the ability to address the shortcomings of RNNs which do not perform well, e.g., when handling long-term dependencies (Graves, 2013). Furthermore, LSTMs avoid the gradient vanishing or exploding problem (Hochreiter, 1998; Gers et al., 1999).

In 1999, a LSTM with a forget gate was introduced which could reset the cell memory. This improved the initial LSTM and became the standard structure of LSTM networks (Gers et al., 1999). In contrast to Deep Feedforward Neural Networks, LSTMs contain feedback connections. Furthermore, they can not only process single data points, such as vectors or arrays, but sequences of data. For this reason, LSTMs are particularly useful for analyzing speech or video data.

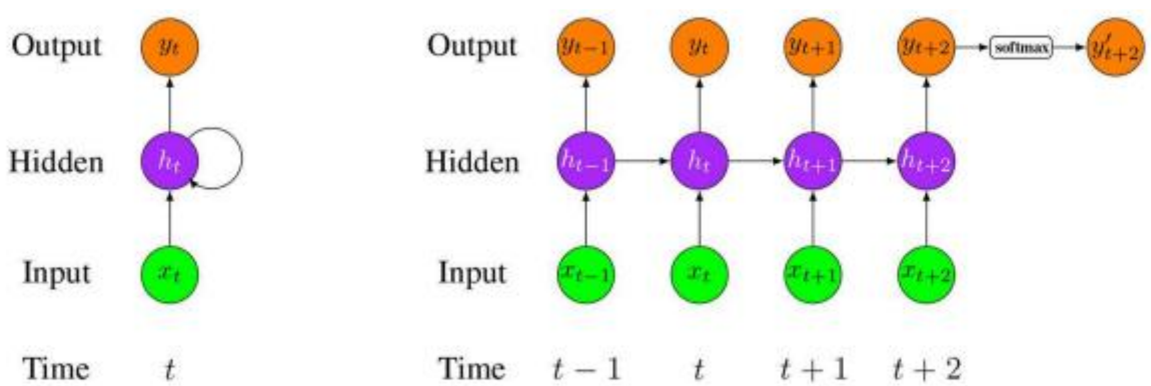

Figure 5: (Left) A folded structure of a LSTM network model. (Right) An unfolded structure of a LSTM network model. xi is the input data at time i and yi is the corresponding output (i is the time step starting from (t − 1)). In this network, only y ′ t+2 activated by softmax function is the final network output.

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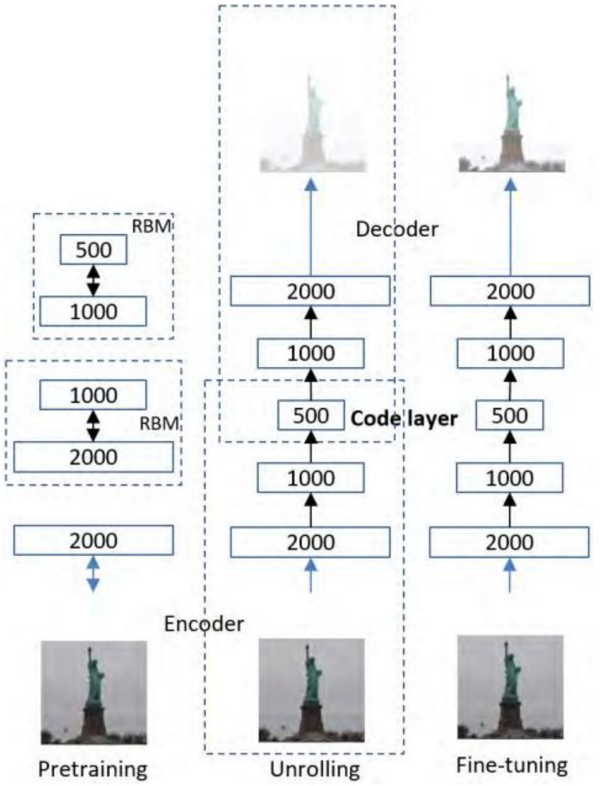

Figure 4: Training stages in autoencoder

These deep learning models play a vital role in modern AI and machine learning research and applications. They have enabled significant advancements in various fields by automatically learning and extracting meaningful patterns and features from data, leading to improved performance and novel insights.

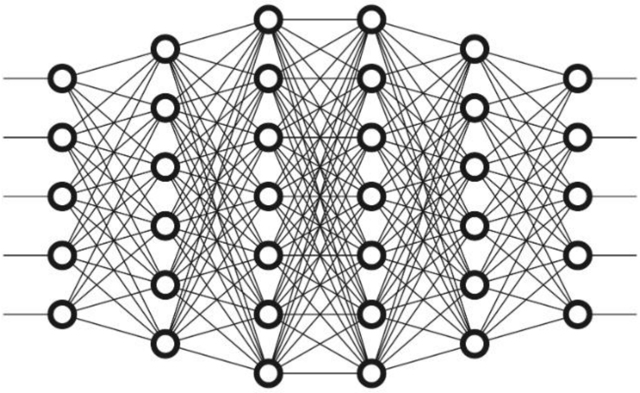

Figure 5: A neural network with 4 hidden layers

The output layer is where the learned representations come together to produce the desired output in above Fig [4,5] depending on the learning problem under consideration.

Although each of these tasks has its own target, there is fundamental overlap in the pipeline implementation of these applications as shown in Fig.[4]. Classification is a concept that categorizes a set of data into classes. Detection is used to locate interesting objects in an image with consideration given to the background. In detection, multiple objects, which could be from dissimilar classes, are surrounded by bounding boxes.

A Deep Belief Network (DBN) is a model that combines different types of neural networks with each other to form a new neural network model. Specifically, DBNs integrate Restricted Boltzmann Machines (RBMs) with Deep Feedforward Neural Networks (D-FFNN). The RBMs form the input unit whereas the D-FFNNs form the output unit. Frequently, RBMs are stacked on top of each other, which means more than one RBM is used sequentially.

This adds to the depth of the DBN. Due to the different nature of the networks RBM and DFFNN, two different types of learning algorithms are used. Practically, the Restricted Boltzmann Machines are used for initializing a model in an unsupervised way. Thereafter, a supervised method is applied for the fine tuning of the parameters (Yoshua, 2009).

- Pre-training Phase: Unsupervised Theoretically, neural networks can be learned by using supervised methods only. However, in practice it was found that such a learning process can be very slow. For this reason, unsupervised learning is used to initialize the model parameters. The standard neural network learning algorithm (backpropagation) was initially only able to learn shallow architectures. However, by using a Restricted Boltzmann Machine for the unsupervised initialization of the parameters one obtains a more efficient training of the neural network.
- Fine-Tuning Phase: Supervised After the initialization of the parameters of the neural network, as described in the previous step, these can now be fine-tuned. For this step, a supervised learning approach is used, i.e., the labels of the samples, omitted in the pre-training phase, are now utilized. For learning the model, one minimizes an error function (also called loss function or sometimes objective function).

Localization is the concept used to locate the object, which is surrounded by a single bounding box. In segmentation (semantic segmentation), the target object edges are surrounded by outlines, which also label them; moreover, fitting a single image (which could be 2D or 3D) onto another refers to registration.

One of the most important and wide-ranging DL applications are in healthcare [25–30]. This area of research is critical due to its relation to human lives. Moreover, DL has shown tremendous performance in healthcare. Therefore, we take DL applications in the medical image analysis field as an example to describe the DL applications.

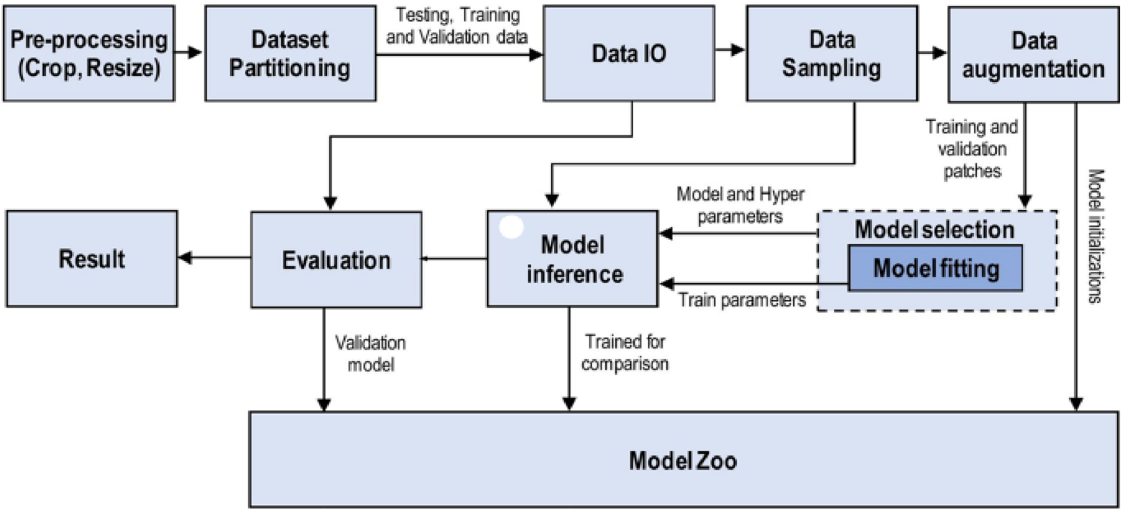

Figure 6: A Workflow of Deep Learning

Various Forms of Data

As DL models learn from data, an in-depth understanding and representation of data are important to build a datadriven intelligent system in a particular application area. In the real world, data can be in various forms, which typically can be represented as below for deep learning modeling.

a) Sequential Data Sequential data is any kind of data where the order matters, i,e., a set of sequences. It needs to explicitly account for the sequential nature of input data while building the model. Text streams, audio fragments, video clips, time-series data, are some examples of sequential data.
b) Image or 2D Data: A digital image is made up of a matrix, which is a rectangular array of numbers, symbols, or expressions arranged in rows and columns in a 2D array of numbers. Matrix, pixels, voxels, and bit depth are the four essential characteristics or fundamental parameters of a digital image.
c) Tabular Data: A tabular dataset consists primarily of rows and columns. Thus tabular datasets contain data in a columnar format as in a database table. Each column (field) must have a name and each column may only contain data of the defined type. Overall, it is a logical and systematic arrangement of data in the form of rows and columns that are based on data properties or features. Deep learning models can learn efficiently on tabular data and allow us to build data-driven intelligent systems.

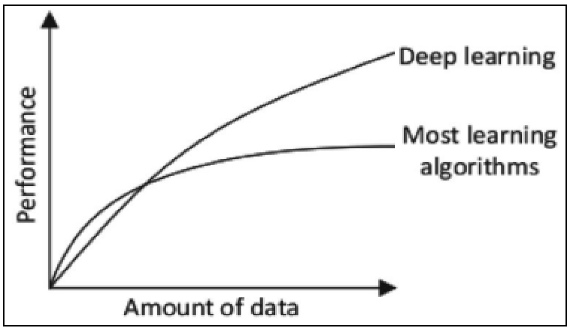

Figure 7: An illustration of the performance comparison between deep learning (DL) and other machine learning (ML) algorithms, where DL modeling from large amounts of data can increase the performance

The above-discussed data forms are common in the real-world application areas of deep learning. Different categories of DL techniques perform differently depending on the nature and characteristics of data, discussed briefly in Section "Deep Learning Techniques and Applications" with a taxonomy presentation. However, in many real-world application areas, the standard machine learning techniques, particularly, logic-rule or tree-based techniques [10,11] perform significantly depending on the application nature. Fig [6] also shows the performance comparison of DL and ML modeling considering the amount of data. In the following, we highlight several cases, where deep learning is useful to solve real-world problems, according to our main focus in this paper.

Table 1: Popular deep learning frameworks and libraries

Framework	Institution	License	1st Release
Caffe	Berkeley AI Research	BSD/ Free	2015
Microsoft Cognitive toolkit	Microsoft	MIT License/ Free	2016
Gluon	AWS & Microsoft	Open Source	2017
Keras	Individual Author	MIT License/ Free	2015
MXNet	Apache Software Foundation	Apache 2.0/ Free	2015
Tensor Flow	Google Brain	Apache 2.0/ Free	2015
Theano	University of Montreal	BSD/ Free	2008
Torch	Ronan Collobert et al	BSD/ Free	2002
PyTorch	Facebook	BSD/ Free	2016
Chainer	Preferred Networks	BSD/ Free	2015
Deep Learning4j	Adam Gibson et al	Apache 2.0/ Free	2014

Table 2: List of popular deep learning models, available learning algorithms (unsupervised, supervised) and software implementations in R or python.

Model	Unsupervised	Supervised	Software
Autoencoder	✓		Keras (Chollet, 2015), R: dimRed (Kraemer et al., 2018), h2o (Candel et al., 2015), RcppDL (Kou and Sugomori, 2014)
Convolutional Deep Belief Network (CDBN)	✓	✓	R & python: TensorFlow (Abadi et al., 2016), Keras (Chollet, 2015), h2o (Candel et al., 2015)
Convolutional Neural Network (CNN)	✓	✓	R & python: Keras (Chollet, 2015) MXNet (Chen et al., 2015), Tensorflow (Abadi et al., 2016), h2O (Candel et al., 2015), fastai (python) (Howard and Gugger, 2018)
Deep Belief Network (DBN)	✓	✓	RcppDL (R) (Kou and Sugomori, 2014), python: Caffee (Jia et al., 2014), Theano (Theano Development Team, 2016), Pytorch (Paszke et al., 2017), R & python: TensorFlow (Abadi et al., 2016), h2O (Candel et al., 2015)
Deep Boltzmann Machine (DBM)		✓	python: boltzmann-machines (Bondarenko, 2017), pydbm (Chimera, 2019)
Denoising Autoencoder (dA)	✓		Tensorflow (R, python) (Abadi et al., 2016), Keras (R, python) (Chollet, 2015), RcppDL (R) (Kou and Sugomori, 2014)
Long short-term memory (LSTM)		✓	rnn (R) (Quast, 2016), OSTSC (R) (Dixon et al., 2017), Keras (R and python) (Chollet, 2015), Lasagne (python) (Dieleman et al., 2015), BigDL (python) (Dai et al., 2018), Caffe (python) (Jia et al., 2014)
Multilayer Perceptron (MLP)		✓	SparkR (R) (Venkataraman et al., 2016), RSNNS (R) (Bergmeir and Benítez, 2012), keras (R and python) (Chollet, 2015), sklearn (python) (Pedregosa et al., 2011), tensorflow (R and python) (Abadi et al., 2016)
Recurrent Neural Network (RNN)		✓	RSNNS (R) (Bergmeir and Benítez, 2012), rnn (R) (Quast, 2016), keras (R and python) (Chollet, 2015)
Restricted Boltzmann Machine (RBM)	✓	✓	RcppDL (R) (Kou and Sugomori, 2014), deepnet (R) (Rong, 2014), pydbm (python) (Chimera, 2019), sklearn (python) (Chimera, 2019), Pylearn2 (Goodfellow et al., 2013), TheanoLM (Enarvi and Kurimo, 2016)

5. Results

The classification performance of a deep network initialized with a SdA is compared to popular classifiers, that is, the quadratic Bayes, k-NN and SVM. For the later, feature extraction using retina and dimensionality reduction using PCA was performed. As for the deep networks, no pre-processing was applied, which is inline with the idea of automatic representation learning. Results were generated using a logistic regression.

Table 2: Comparison between quadratic bayes, k-NN, SVM and SdA on MNIST.

Classifier comparison on MNIST

Classifier	Pre-processing	Error rate
Quadratic Bayes	Retina 10x10 + PCA	4.17%
k-NN	Retina 10x10 + PCA	3.37%
SVM	Retina 10x10 + PCA	1.94%
3 layers SdA + logistic regression	None	1.41%
3 layers SdA + SVM	None	1.16%

6. Deep Learning Application

Domain	Applications	Notable Models/ Architectures	Key Advantages	Challenges
Computer Vision	Image recognition, object detection, facial recognition, image generation	CNNs (e.g., ResNet, VGG), YOLO, Faster R-CNN	High accuracy, automated feature extraction, real-time processing	Need for large labeled datasets, interpretability issues.
Natural Language	Language translation, sentiment analysis,	Transformers (e.g., BERT, GPT),	Contextual understanding, handling	Ambiguity, bias, context dependence,
Processing	chatbots, text generation	LSTM, GRU	vast amounts of text data.	pretraining challenges.
Autonomous Systems	Self-driving cars, drones, robotics	CNNs, RNNs	Perception, decision-making, navigation in dynamic environments.	Safety concerns, real-world variability, ethical dilemmas.
Healthcare	Medical image analysis, disease diagnosis, drug discovery, patient outcome prediction	CNNs, GANs Autoencoders, RNNs, Transformers	Early disease detection, personalized treatment plans.	Data privacy, interpretability, model robustness.
Finance	Stock market prediction, fraud detection, credit risk assessment	CNNs, LSTM Transformers (BERT for sentiment)	Pattern recognition, anomaly detection, risk assessment.	Data imbalance, dynamic market conditions, interpretability.
Entertainment	Video and audio analysis, music generation, content recommendation	CNNs, RNNs GANs, LSTM	Content recommendation, content generation.	Copyright issues, algorithmic biases, creative control.
Manufacturing	Quality control, predictive maintenance, process optimization	CNNs, RNNs Autoencoders, GANs	Defect detection, optimization, efficient resource allocation.	Data quality, scalability, real-time processing.
Energy	Energy consumption prediction, fault detection in power systems	LSTM, CNNs Transformers (for time series)	Predictive maintenance, optimization of energy resources.	Data variability, model accuracy, scalability.

DL has become an incredibly popular type of ML algorithm in recent years due to the huge growth and evolution of the field of big data [11,12]. It is still in continuous development regarding novel performance for several ML tasks [12, 13,14,15] and has simplified the improvement of many learning fields [16,17], such as image super-resolution [18], object detection [19,20], and image recognition. Recently, DL performance has come to exceed human performance on tasks such as image classification (Fig. 5)

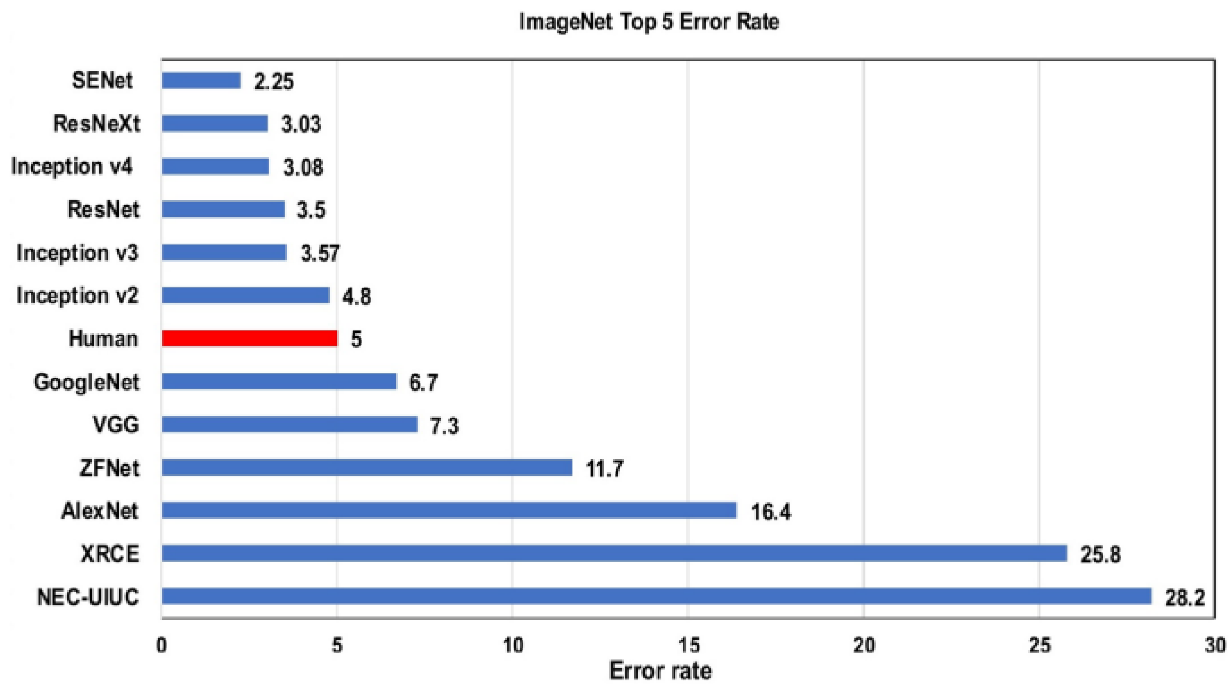

Figure 8: Deep learning performance compared to human

Presently, various DL applications are widespread around the world. These applications include healthcare, social network analysis, audio and speech processing (like recognition and enhancement), visual data processing methods (such as multimedia data analysis and computer vision), and NLP (translation and sentence classification), among others (Fig. 8,9) [21-24]. These applications have been classified into five categories: classification, localization, detection, segmentation, and registration.

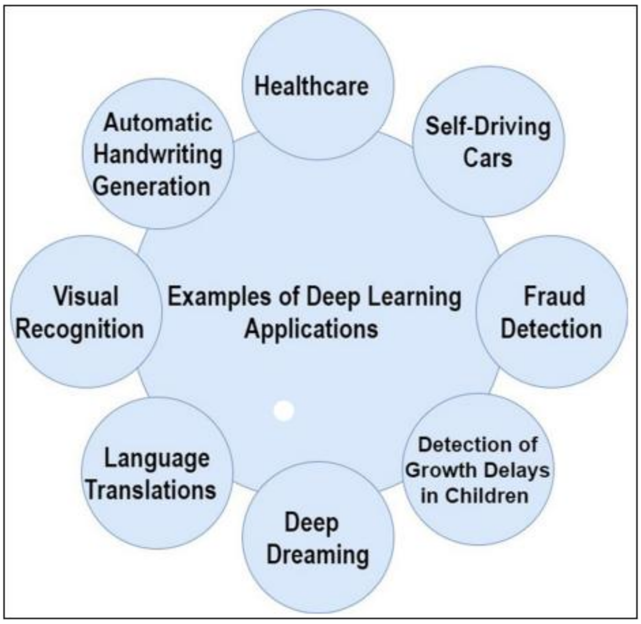

Figure 9: Application of Deep learning

In the 1990s, the study of neural networks has gained great progress, but compared with support vector machine, two crucial problems remained. First, the algorithm is usually limited to the local optimal solution rather than the overall optimal solution. Second, its training time is so long that may lead to overfit which makes the program regard noise as valid signals.

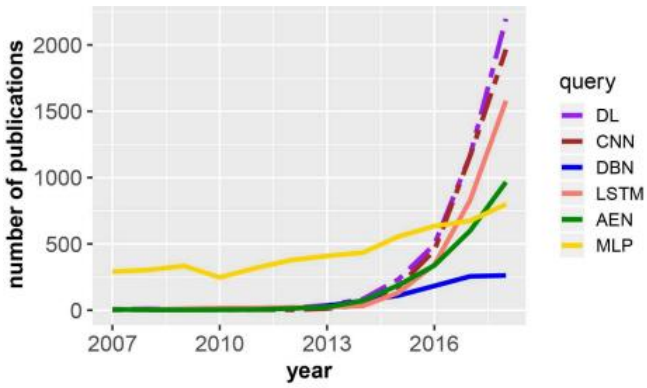

Figure 10: Number of publications in dependence on the publication year for DL, deep learning; CNN, convolutional neural network; DBN, deep belief network; LSTM, long short-term memory; AEN, autoencoder; and MLP, multilayer perceptron. The legend shows the search terms used to query the Web of Science publication database. The two dashed lines are scaled by a factor of 5 (deep learning) and 3 (convolutional neural network).

In Fig[10] , we show the evolution of publications related to deep learning from the Web of Science publication database. Specifically, the figure shows the number of publications in dependence on the publication year for DL, deep learning; CNN, convolutional neural network; DBN, deep belief network; LSTM, long short-term memory; AEN, autoencoder; and MLP, multilayer perceptron. The two dashed lines are scaled by a factor of 5 (deep learning) and 3 (convolutional neural network), i.e., overall, for deep learning we found the majority of publications (in total 30, 230). Interestingly, most of these are in computer science (52.1%) and engineering (41.5%). In application areas, medical imaging (6.2%), robotics (2.6%), and computational biology (2.5%) received most attention. These observations are a reflection of the brief history of deep learning indicating that the methods are still under development. In the following sections, we will discuss all of these methods in more detail because they represent the core methodology of deep learning. In addition, we present background information about general artificial neural networks as far as this is needed for a better understanding of the DL methods.

7. Development Trends, Application And Challenges

Deep learning has been widely used to solve image and speech problems in the background of big data, but there are still challenges in the future development.

On the one hand, the statistics of deep learning training is still very difficult, because it is hard to estimate the basic requirements of training about how much resources to use and understand complex samples. Since the models of deep learning are non convex functions, research in this area is extremely difficult. Besides, nowadays , the data for feature learning[39] is marked, but the data in real world is not. If each data is to be labeled, it is clear that the workload will be incalculable. Therefore, in the future, we will pay attention to the operation for unmarked data, and let the machine do tag processing. Another problem is the trade-off among the size of the model, the speed of the training and the accuracy of the training. Generally, for the same data set, the greater the scale, the higher the training accuracy, and the slower the relative training speed. The offline processing technology now has low efficiency and low accuracy because of the problem about setting parameters and so on. Therefore, in the future development, we should consider whether there is a new hierarchical model, which can keep the traditional method clearly and also have good theoretical analysis ability and speed. In addition, more research should be done on how to use deep models to represent semantics and other structured information. Human language abilities lag far behind visual and auditory abilities. Many animals have similar situations. Therefore, the extreme excellence of language is still an unknown area for the neural network. And the solution of this problem will definitely lead the development of artificial intelligence.

Deep learning is a technology that continues to mature, and has clearly been applied to a multitude of applications and domains to great effect. While the full-scale adoption of deep learning technologies in industry is ongoing, measured steps should be taken to ensure appropriate application of deep learning, as the subversion of deep learning models may result in significant loss of monetary value, trust, or even life in extreme cases. In this survey, we have provided an overview of deep learning operation, distinguishing deep learning from traditional shallow learning methods, and outlining prominent structural implementations. We have reviewed deep learning architectures in detail based on learning mechanisms (supervised, unsupervised, and reinforcement) and the target output structures, and provided typical examples in each case. We have also introduced many common and widely adopted deep learning frameworks, and considered them from the perspectives of design, extensibility and comparative efficacy. It is worth mentioning that each of the frameworks implements the basic elements of deep learning in different ways using different libraries, are optimized for different hardware systems, and provide varying degrees of control over model design.

Secure Deep Learning Given the increasing number of devices, operating systems, and communication protocols that abound in IoT, security is an ever-ballooning problem Securing the data, operation, and mechanisms of deep learning are all the more relevant in considering edge computing, which can be a viable computing infrastructure to provision deep learning schemes, supporting a variety of smart-world systems (smart cities, smart manufacturing, smart grid, smart transportation, and many others). As computing nodes will be more dispersed and local to the user, they will also have fewer resources and be more available to would-be adversaries. The investigation and application of increasingly sophisticated security mechanisms, such as homomorphic encryption, are thus significant.

For example, Li et al. proposed multiple schemes for machine learning on multi-key homomorphic encrypted data in the cloud. In the first scheme, deep learning is conducted on multiple users' data who share the same public key. In the second scheme, using double decryption, training is performed on ciphertexts of users with different public keys. While these are novel methods that leverage the state-of-the-art in security research, encrypting not only data, but computation as well, they can still be considered as expansions of traditional security techniques.

In exception to traditional mechanisms, attacks that seek to undermine the output of deep learning systems have recently received deeper consideration. Indeed, the widespread adoption of machine learning is cause for concern, as attacks that are solely intended to thwart the normal operation of the learning network can lead to catastrophic harm. For instance, a recent work by Yuan et al. specifically investigated the space of these attacks that target only the inference mechanism through adversarial input. The authors classified no less than sixteen different attack methods, which have been shown to be effective against various targets, including subverting segmentation (removal of objects from detection) and facial recognition. This is similar to an investigation by Huang et al from 2011, which investigated security in machine learning and provided a taxonomy for causative and exploratory attacks, and formulated game-theory-based formalisms to understand each attack. Nonetheless, the latter focused on the shallow learning methods of the time.

In statistics, the field of experimental design is concerned with assessing if the available sample sizes are sufficient to conduct a particular analysis (for a practical example see Stupnikov et al., 2016). In contrast, for all methods discussed in this paper, we assumed that we are in the big data domain implying sufficient samples. This corresponds to the ideal case. However, we would like to point out that for practical applications, one needs to assess this situation case-by-case to ensure the available data (respectively the sample sizes) are sufficient to use deep learning models.

Unfortunately, this issue is not well-represented in the current literature. As a ruleof-thumb, deep learning models usually perform well for tens of thousands of samples but it is largely unclear how they perform in a small data setting. This leaves it to the user to estimate learning curves of the generalization error for a given model to avoid spurious results (Emmert-Streib and Dehmer, 2019b). As an example to demonstrate this problem, we conducted an analysis to explore the influence of the sample size on the accuracy of the classification of the EMNIST data. EMNIST (Extended MNIST) (Cohen et al., 2017) consists of 280, 000 handwritten characters (240, 000 training samples and 40, 000 test samples) for 10 balanced classes (0–9). We used a multilayered Long Short-Term Memory (LSTM) model for the 10-class handwritten digit classification task. The model we used is a four-layer network (three hidden layers and one fully connected layer), and each hidden layer contains 200 neurons. For this analysis, we set the batch size to 100 and the training samples were randomly drawn if the number of training samples was < 240, 000 (subsampling).

8. Future Scope

Finally, we would like to emphasize that there are additional but more advanced models of deep learning networks, which are outside the core architectures. For instance, deep learning and reinforcement learning have been combined with each other to form deep reinforcement learning (Mnih et al., 2015; Arulkumaran et al., 2017; Henderson et al., 2018). Such models have found application in problems from robotics, games and healthcare.

Another example for an advanced model is a graph CNN, which is particularly suitable when data have the form of graphs (Henaff et al., 2015; Wu et al., 2019). Such models have been used in natural language processing, recommender systems, genomics and chemistry (Li et al., 2018; Yao et al., 2019).

Lastly, a further advanced model is a Variational Autoencoder (VAE) (An and Cho, 2015; Doersch, 2016). Put simply, a VAR is a regularized Autoencoder that uses a distribution over the latent spaces as encoding for the input, instead of a single point. The major application of VAE is as a generative model for generating similar data in an unsupervised manner, e.g., for image or text generation.

9. Conclusion

In this paper, we provided a thorough overview of the neural networks and deep neural networks. Also took a deeper dive into the well-known training algorithms and architectures. We highlighted their shortcomings, e.g., getting stuck in the local minima, overfitting and training time for large problem sets. We examined several state-of-the-art ways to overcome these challenges with different optimization methods. We investigated adaptive learning rates and hyperparameter optimization as effective methods to improve the accuracy of the network. We surveyed and reviewed several recent papers, studied them and presented their implementations and improvements to the training process. We also included tables to summarize the content in a concise manner. The tables provide a full view on how different aspects of deep learning are correlated. Deep Learning is still in its nascent stage. There is tremendous opportunity for exploitation of current algorithms/architectures and further exploration of optimization methods to solve more complex problems. Training is currently constrained by overfitting, training time and is highly susceptible to getting stuck in local minima. If we can continue to overcome these challenges, deep learning networks will accelerate breakthroughs across all applications of machine learning and artificial intelligence.

Side-channel analysis (SCA) is launched by exploiting the information leaking from the implementation a cryptographic algorithm, e.g., power consumption information. Recently, deep learning-based SCA techniques have also facilitated SCA against software and hardware implementations of various cryptographic algorithms. In this work, we perform SCA using various deep learning (DL) techniques such as Multi-layered Perceptron (MLP), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) on the datasets collected from hardware and software platforms. The objective of this work is to identify the performance of DL techniques in performing SCA for secret key recovery and finding out the best settings for the model to optimize the attack performance in terms of on computation time and SCA efficiency. In our study, we have focused on two open-source AES-128 encryption algorithm databases, ASCAD and DPA contest v2 (DPAv2), where ASCAD database consists of the power traces captured from a software implementation of the AES and DPAv2 database consists of the power traces captured a hardware implementation of the AES. For the first time, we applied hyperparameter tuning with Bayesian Optimization and distributed computing on ASCAD database and we investigated the impact of MLP and RNN along with the distributed computing and hyperparameter tuning with Bayesian optimization on DPAv2 database. Our results show that the CNNs are the best models for performing the attack on software implementation while MLPs are the best for attacking hardware implementation of cryptographic algorithms.

Currently, a variety of DL methods are adopted for geotechnical engineering practices, such as tunnel construction, slope displacement prediction, landslide susceptibility evaluation and pile bearing capability assessment. Essentially based on the powerful nonlinear refection and training function of deep neural networks, DL can progressively extract higher level features from the raw data while both the real-time and historical data can be utilized as inputs to develop DL models. Taking the advantages of efficiently processing increasing amount of data as well as requiring less subjective judgement, DL has outperformed over other ML methods for geotechnical applications. Accordingly, this study presented a systematic review on different DL approaches applied in the geotechnical field and bridged the knowledge gap by performing a structured review of relevant literature focus on the use of DL applications in recent years. A summary of annual distribution of published journal articles focus on the DL application is depicted from the web of science database. Meanwhile, the distribution of selected articles amongst the contributive journals and corresponding publications are presented in the form of tables and pie charts. Furthermore, all selected papers were grouped into different categories considering the DL adopted. By reviewing the application of DL technology in various geotechnical aspects, the deep FNN, RNN and its optimized versions LSTM, CNN and GAN are widely used in geotechnical engineering, hence, the basic architecture of these most popular DL methods are also mainly introduced. With respect to the specific applications, the literature review indicates that FNN has the longest development time and is the most widely used in the field of geotechnical engineering, while deep FNN is rarely used considering the limitation of the ability to improve the estimation results. RNN is more suitable for time series problem, and its evolutionary version LSTM shows a more satisfactory performance for long-term prediction, so it is widely used in landslide deformation prediction, tunnel boring machine parameters prediction. CNN is better at solving image process research, such as porous media reconstruction. For the unsupervised learning algorithm GAN, which is appeared in the latest years, its application in the geotechnical field is limited. However, its great potential lies in combining with other supervised learning algorithms due to its excellent generating ability.

Through the results of this review, it is evident that the adoption of DL algorithms for geotechnical engineering is an emerging field of study given the increasing trend in annual publications. As more monitoring data collected from different sites, the efficiency of DL methods may aid intelligent early warning by providing data driven inputs. Moreover, it can also be concluded that based on the development of technologies required for storing, computing, processing, analyzing, and visualizing of big data, DL theory may be able to extract more valuable knowledge and can better tap the potential links between information. Therefore, the combination of big data and DL is becoming the new trend of AI in geotechnical engineering.

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