A Survey on Deep Learning: Algorithms, Techniques, and Applications

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The field of machine learning is witnessing its golden era as deep learning slowly becomes the leader in this domain. Deep learning uses multiple layers to represent the abstractions of data to build computational models. Some key enabler deep learning algorithms such as generative adversarial networks, convolutional neural networks, and model transfers have completely changed our perception of information processing. However, there exists an aperture of understanding behind this tremendously fast-paced domain, because it was never previously represented from a multiscope perspective. The lack of core understanding renders these powerful methods as black-box machines that inhibit development at a fundamental level. Moreover, deep learning has repeatedly been perceived as a silver bullet to all stumbling blocks in machine learning, which is far from the truth. This article presents a comprehensive review of historical and recent state-of-the-art approaches in visual, audio, and text processing; social network analysis; and natural language processing, followed by the in-depth analysis on pivoting and groundbreaking advances in deep learning applications. It was also undertaken to review the issues faced in deep learning such as unsupervised learning, black-box models, and online learning and to illustrate how these challenges can be transformed into prolific future research avenues.

CCS Concepts: • **Computing methodologies** → **Neural networks**; **Machine learning algorithms**; *Parallel algorithms*; *Distributed algorithms*; • **Theory of computation** → *Machine learning theory*;

Additional Key Words and Phrases: Deep learning, neural networks, machine learning, distributed processing, big data, survey

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1 INTRODUCTION

In recent years, machine learning has become more and more popular in research and has been incorporated in a large number of applications, including multimedia concept retrieval, image classification, video recommendation, social network analysis, text mining, and so forth. Among various machine-learning algorithms, "deep learning," also known as representation learning [29], is widely used in these applications. The explosive growth and availability of data and the remarkable advancement in hardware technologies have led to the emergence of new studies in distributed and deep learning. Deep learning, which has its roots from conventional neural networks, significantly outperforms its predecessors. It utilizes graph technologies with transformations among neurons to develop many-layered learning models. Many of the latest deep learning techniques have been presented and have demonstrated promising results across different kinds of applications such as Natural Language Processing (NLP), visual data processing, speech and audio processing, and many other well-known applications [169, 170].

Traditionally, the efficiency of machine-learning algorithms highly relied on the goodness of the representation of the input data. A bad data representation often leads to lower performance compared to a good data representation. Therefore, feature engineering has been an important research direction in machine learning for a long time, which focuses on building features from raw data and has led to lots of research studies. Furthermore, feature engineering is often very domain specific and requires significant human effort. For example, in computer vision, different kinds of features have been proposed and compared, including Histogram of Oriented Gradients (HOG) [27], Scale Invariant Feature Transform (SIFT) [102], and Bag of Words (BoW). Once a new feature is proposed and performs well, it becomes a trend for years. Similar situations have happened in other domains including speech recognition and NLP.

Comparatively, deep learning algorithms perform feature extraction in an automated way, which allows researchers to extract discriminative features with minimal domain knowledge and human effort [115]. These algorithms include a layered architecture of data representation, where the high-level features can be extracted from the last layers of the networks while the low-level features are extracted from the lower layers. These kinds of architectures were originally inspired by Artificial Intelligence (AI) simulating its process of the key sensorial areas in the human brain. Our brains can automatically extract data representation from different scenes. The input is the scene information received from eyes, while the output is the classified objects. This highlights the major advantage of deep learning—i.e., it mimics how the human brain works.

With great success in many fields, deep learning is now one of the hottest research directions in the machine-learning society. This survey gives an overview of deep learning from different perspectives, including history, challenges, opportunities, algorithms, frameworks, applications, and parallel and distributed computing techniques.

1.1 History

Building a machine that can simulate human brains had been a dream of sages for centuries. The very beginning of deep learning can be traced back to 300 B.C. when Aristotle proposed "associationism," which started the history of humans' ambition in trying to understand the brain, since such an idea requires the scientists to understand the mechanism of human recognition systems. The modern history of deep learning started in 1943 when the McCulloch-Pitts (MCP) model was introduced and became known as the prototype of artificial neural models [107]. They created a computer model based on the neural networks functionally mimicking neocortex in human brains [138]. The combination of the algorithms and mathematics called "threshold logic" was used in their model to mimic the human thought process but not to learn. Since then, deep learning has evolved steadily with a few significant milestones in its development.

After the MCP model, the Hebbian theory, originally used for the biological systems in the natural environment, was implemented [134]. After that, the first electronic device called "perceptron" within the context of the cognition system was introduced in 1958, though it is different from typical perceptrons nowadays. The perceptron highly resembles the modern ones that have the power to substantiate associationism. At the end of the first AI winter, the emergence of "backpropagandists" became another milestone. Werbos introduced backpropagation, the use of errors in training deep learning models, which opened the gate to modern neural networks. In 1980, "neocogitron," which inspired the convolutional neural network, was introduced [40], while Recurrent Neural Networks (RNNs) were proposed in 1986 [73]. Next, LeNet made the Deep Neural Networks (DNNs) work practically in the 1990s; however, it did not get highly recognized [91]. Due to the hardware limitation, the structure of LeNet is quite naive and cannot be applied to large datasets.

Around 2006, Deep Belief Networks (DBNs) along with a layer-wise pretraining framework were developed [62]. Its main idea was to train a simple two-layer unsupervised model like Restricted Boltzmann Machines (RBMs), freeze all the parameters, stick a new layer on top, and train just the parameters for the new layer. Researchers were able to train neural networks that were much deeper than the previous attempts using such a technique, which prompted a rebranding of neural networks to deep learning. Originally from Artificial Neural Networks (ANNs) and after decades of development, deep learning now is one of the most efficient tools compared to other machine-learning algorithms with great performance. We have seen a few deep learning methods rooted from the initial ANNs, including DBNs, RBMs, RNNs, and Convolutional Neural Networks (CNNs) [77, 86].

While Graphics Processing Units (GPUs) are well known for their performance in computing large-scale matrices in network architectures on a single machine, a number of distributed deep learning frameworks have been developed to speed up the training of deep learning models [8, 108, 171]. Because the vast amounts of data come without labels or with noisy labels, some research studies focus more on improving noise robustness of training modules using unsupervised or semisupervised deep learning techniques. Since most of the current deep learning models only focus on a single modality, this leads to a limited representation of real-world data. Researchers are now paying more attention to a cross-modality structure, which may yield a huge step forward in deep learning [76].

One recent inspirational application of deep learning is Google AlphaGo, which completely shocked the world at the start of year 2017 [50]. Under the pseudonym name "master," it won 60 online games in a row against human professional Go players, including three victories over Ke Jie, from December 29, 2016, to January 4, 2017. AlphaGo is able to defeat world champion Go players because it uses the modern deep learning algorithms and sufficient hardware resources.

1.2 Research Objectives and Outline

While deep learning is considered a huge research field, this article aims to draw a big picture and shares research experience with peers. While some previous survey papers only focused on a certain scope in deep learning [36, 70], the novelty of this article is that it focuses on different aspects of deep learning by presenting a review of the top-level papers, the authors' experience, and the breakthroughs in research on and applications in deep neural networks.

The topmost challenge that deep learning faces today is to train the massive datasets available at hand. As the datasets become bigger, more diverse, and more complex, deep learning has been in its path to be a critical tool to cater to big data analysis. In our survey, challenges and opportunities in key areas of deep learning are raised that require first-priority attention including parallelism, scalability, power, and optimization. To solve the aforementioned issues, different

Table 1. Summary of the Deep Learning (DL) Networks

DL Networks	Descriptive Key Points	Papers
RvNN	Uses a tree-like structure Preferred for NLP	Goller et al. 1996 [47], Socher et al. 2011 [146]
RNN	Good for sequential information Preferred for NLP & speech processing	Cho et al. 2014 [20], Li et al. 2015 [93]
CNN	Originally for image recognition Extended for NLP, speech processing, and computer vision	LeCunn et al. 1995 [89], Krizhevsky et al. 2012 [86], Kim 2014 [79], Abdel-Hamid et al. 2014 [2]
DBN	Unsupervised learning Directed connections	Hinton 2009 [61], Hinton et al. 2012 [60]
DBM	Unsupervised learning Composite model of RBMs Undirected connections	Salakhutdinov et al. 2009 [135], Salakhutdinov et al. 2012 [136]
GAN	Unsupervised learning Game-theoretical framework	Goodfellow et al. 2014 [49], Radford et al. 2015 [130]
VAE	Unsupervised learning Probabilistic graphical model	Kingma et al. 2013 [81]

kinds of deep networks are introduced in different domains such as RNNs for NLP and CNNs for image processing. The article also introduces and compares popular deep learning tools including Caffe, DeepLearning4j, TensorFlow, Theano, and Torch and the optimization techniques in each deep learning tool. In addition, various deep learning applications are reviewed to help other researchers expand their view in deep learning.

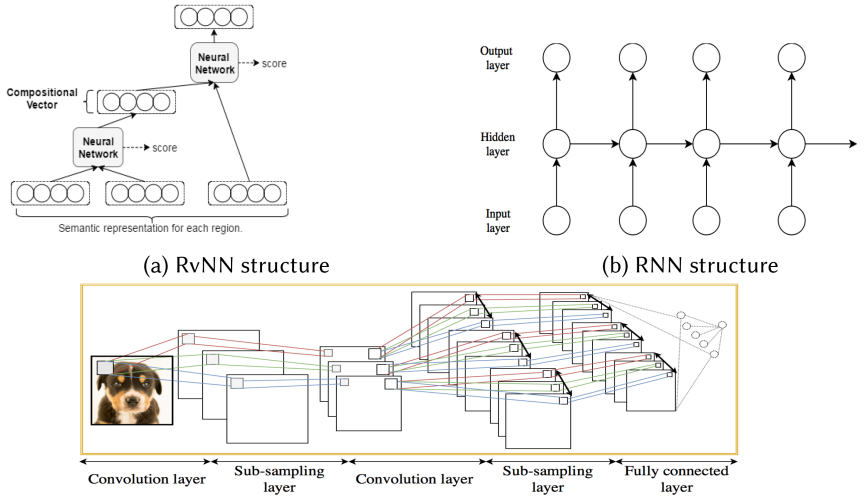
The rest of this article is organized as follows. In Section 2, popular deep learning networks are briefly presented. Section 3 discusses several algorithms, techniques, and frameworks in deep learning. As deep learning has been used from NLP to speech and image recognition as well as the industry-focused applications, a number of deep learning applications are provided in Section 4. Section 5 points out the challenges and potential research directions in the future. Finally, Section 6 concludes this article.

2 DEEP LEARNING NETWORKS

In this section, several popular deep learning networks such as Recursive Neural Network (RvNN), RNN, CNN, and deep generative models are discussed. However, since deep learning has been growing very fast, many new networks and new architectures appear every few months, which is out of the scope of this article. Table 1 contains a summary of the deep learning networks introduced in this section, their major key points, and the most representative papers.

2.1 Recursive Neural Network (RvNN)

RvNN can make predictions in a hierarchical structure as well as classify the outputs using compositional vectors. The development of an RvNN was mainly inspired by Recursive Autoassociative Memory (RAAM) [47], an architecture created to process objects that were structured in an arbitrary shape, such as trees or graphs. The approach was to take a recursive data structure of variable size and generate a fixed-width distributed representation. The Backpropagation Through



(a) RvNN structure

(b) RNN structure

(c) A simple CNN framework for image classification

Fig. 1. RvNN, RNN, and CNN architectures.

Structure (BTS) learning scheme was introduced to train the network [47]. BTS follows an approach similar to the standard backpropagation algorithm and is also able to support a tree-like structure. The network is trained by autoassociation to reproduce the pattern of the input layer at the output layer.

RvNN has been especially successful in NLP. In 2011, Socher et al. [146] proposed an RvNN architecture that can handle the inputs of different modalities. [146] shows two examples of using RvNN to classify natural images and natural language sentences. While an image is separated into different segments of interest, a sentence is divided into words. RvNN calculates the score of a possible pair to merge them and build a syntactic tree. For each pair of units, RvNN computes a score for the plausibility of the merge. The pair with the highest score is then combined into a compositional vector. After each merge, RvNN will generate (1) a larger region of multiple units, (2) a compositional vector representing the region, and (3) the class label (e.g., if both units are two noun words, the class label for the new region would be a noun phrase). The root of the RvNN tree structure is the compositional vector representation of the entire region. Figure 1(c) shows an example RvNN tree.

2.2 Recurrent Neural Network (RNN)

Another widely used and popular algorithm in deep learning, especially in NLP and speech processing, is RNN [20]. Unlike traditional neural networks, RNN utilizes the sequential information in the network. This property is essential in many applications where the embedded structure in the data sequence conveys useful knowledge. For example, to understand a word in a sentence, it is necessary to know the context. Therefore, an RNN can be seen as short-term memory units that include the input layer x, hidden (state) layer s, and output layer y.

Figure 1(b) depicts a typical unfolded RNN diagram for an input sequence. In [124], three deep RNN approaches including deep "Input-to-Hidden," "Hidden-to-Output," and "Hidden-to-Hidden" are introduced. Based on these three solutions, a deep RNN is proposed that not only takes advantage of a deeper RNN but also reduces the difficult learning in deep networks.

One main issue of an RNN is its sensitivity to the vanishing and exploding gradients [46]. In other words, the gradients might decay or explode exponentially due to the multiplications of lots of small or big derivatives during the training. This sensitivity reduces over time, which means the network forgets the initial inputs with the entrance of the new ones. Therefore, Long Short-Term Memory (LSTM) [93] is utilized to handle this issue by providing memory blocks in its recurrent connections. Each memory block includes memory cells that store the network temporal states. Moreover, it includes gated units to control the information flow. Furthermore, residual connections in very deep networks [58] can alleviate the vanishing gradient issue significantly, which is further discussed in Section 4.2.1.

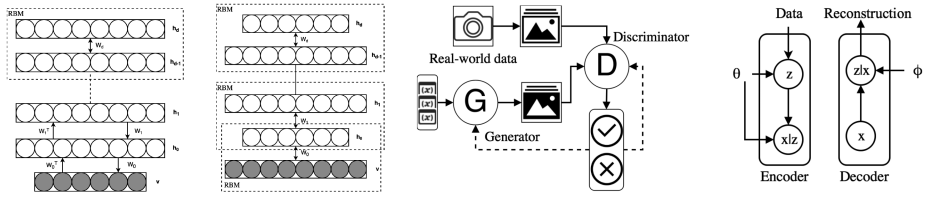
2.3 Convolutional Neural Network (CNN)

CNN is also a popular and widely used algorithm in deep learning [89]. It has been extensively applied in different applications such as NLP [181], speech processing [26], and computer vision [86], to name a few. Similar to the traditional neural networks, its structure is inspired by the neurons in animal and human brains. Specifically, it simulates the visual cortex in a cat's brain containing a complex sequence of cells [67]. As described in [48], CNN has three main advantages, namely, parameter sharing, sparse interactions, and equivalent representations. To fully utilize the two-dimensional structure of an input data (e.g., image signal), local connections and shared weights in the network are utilized, instead of traditional fully connected networks. This process results in very fewer parameters, which makes the network faster and easier to train. This operation is similar to the one in the visual cortex cells. These cells are sensitive to small sections of a scene rather than the whole scene. In other words, the cells operate as local filters over the input and extract spatially local correlation existing in the data.

In typical CNNs, there are a number of convolutional layers followed by pooling (subsampling) layers, and in the final stage layers, fully connected layers (identical to Multilayer Perceptron (MLP)) are usually used. Figure 1(c) shows an example CNN architecture for image classification. The layers in CNNs have the inputs x arranged in three dimensions, $m \times m \times r$, where m refers to the height and width of the input, and r refers to the depth or the channel numbers (e.g., $r = 3$ for an RGB image). In each convolutional layer, there are several filters (kernels) k of size $n \times n \times q$. Here, n should be smaller than the input image, but q can be either smaller or the same size as r. As mentioned earlier, the filters are the base of local connections that are convolved with the input and share the same parameters (weight W^k and bias b^k) to generate k feature maps (h^k), each of size $m - n - 1$. Similar to MLP, the convolutional layer computes a dot product between the weights and its inputs (as illustrated in Equation (1)), but the inputs are small regions of the original input volume. Then, an activation function f or a nonlinearity is applied to the output of the convolutional layers:

$$h^k = f(W^k * x + b^k). \tag{1}$$

Thereafter, in the subsampling layers, each feature map is downsampled to decrease the parameters in the network, speeds up the training process, and hence controls overfitting. The pooling operation (e.g., average or max) is done over a $p \times p$ (where p is the filter size) contiguous region for all feature maps. Finally, the final stage layers are usually fully connected as seen in the regular neural networks. These layers take previous low-level and midlevel features and generate the high-level abstraction from the data. The last layer (e.g., Softmax or SVM) can be used to generate the classification scores, where each score is the probability of a certain class for a given instance.



(a) DBN (b) DBM (c) GAN (d) VAE

Fig. 2. The structure of generative models.

2.4 Deep Generative Networks

Here, four deep generative networks such as DBN, Deep Boltzmann Machine (DBM), Generative Adversarial Network (GAN), and Variational Autoencoder (VAE) are discussed. DBN [61] is a hybrid probabilistic generative model in which a typical RBM with undirected connections is formed by the top two layers, and the lower layers use directed connections to receive inputs from the layer above. The lowest layer, which is the visible layer, represents the states of the input units as a data vector. A DBN learns to probabilistically reconstruct its inputs in an unsupervised approach, while the layers act as the feature detectors on the inputs. Moreover, a further training process in a supervised way gives the DBN the capacity to perform the classification tasks. The DBN resembles a composition of several RBMs [144], where each subnetwork's hidden layer can be viewed as a visible layer for the next subnetwork. Figure 2(a) illustrates the structure of a DBN.

RBMs are generative stochastic artificial neural networks that output a probability distribution of learned inputs. An energy configuration is defined in Equation (2) to calculate the probability distribution based on the connection weights and the unit biases by taking the state vectors $\mathbf{v}$ from the visible layer:

$$E(\mathbf{v}, \mathbf{h}) = -\mathbf{a}^{\mathrm{T}}\mathbf{v} - \mathbf{b}^{\mathrm{T}}\mathbf{h} - \mathbf{v}^{\mathrm{T}}\mathbf{W}\mathbf{h}, \tag{2}$$

where $\mathbf{h}$ is the binary configuration of the hidden layer units, and $\mathbf{a}$ and $\mathbf{b}$ refer to the biases of the visible and hidden units, respectively. A matrix $\mathbf{W}$ represents the connection weights between the layers. This energy function provides a probability between each possible visible and hidden vector pair using Equation (3):

$$P(\mathbf{v}, \mathbf{h}) = \frac{e^{-E(\mathbf{v},\mathbf{h})}}{S}, \tag{3}$$

where S is the partition function defined as the sum of $e^{-E(\mathbf{v},\mathbf{h})}$ over all possible configurations (generally, a normalizing constant to guarantee the probability distribution aggregated to 1).

The DBN includes a greedy algorithm to improve the generative model by allowing each subnetwork to sequentially receive different representations of the data, since an RBM will not be able to model the original data ideally. Once the initial weights $\mathbf{W}_0$ are learned, the data can be mapped through the transposed weighing matrix $\mathbf{W}_0^{\mathrm{T}}$ to create the higher-level "data" for the next layer. As shown in [62], the log probability of each input data vector is bounded under the approximating distribution. Furthermore, at each time adding a new layer into the DBN, the variational bounds on the deeper layer are improved compared to the previous one that initializes the new RBM block in the right direction.

Like a DBN, the DBM [135] can learn complex internal representations. It is considered as a robust deep learning model for speech and object recognition tasks. On the other hand, unlike a DBN, the approximate reasoning procedure allows a DBM to handle ambiguous inputs robustly. Figure 2(b) presents the architecture of a DBM, which is a composite model of RBMs. It also clearly

shows how a DBM differs from a DBN. The lower layers in a DBN build a directed belief network, instead of the undirected RBMs as in a DBM.

The layer-wise greedy training algorithm for a DBM can be easily calculated by modifying the procedure in a DBN. A factorial approximation to the posterior can take either the result from the first RBM or the probability from the second layer. Taking a geometric average of these two distributions would be a better idea to balance the approximations to the posterior, which uses $1/2\,\mathbf{W}_0$ bottom-up and $1/2\,\mathbf{W}_1$ (the second layer weights) top-down.

GAN [49] consists of a generative model G and a discriminative model D. While G captures the distribution p_g over the real data t locally, D tries to differentiate a sample that comes from the modeling data m rather than p_g, represented by p_m. In every iteration of the backpropagation, the generator and the discriminator, like in a game of cat and mouse, compete between each other. While the generator is trying to generate more realistic data to fool and confuse the discriminator, the latter tries to identify the real data from the fake ones that were generated by G. The two-player minimax game is established with a value function $V(G, D)$:

$$\min_G \max_D V(G, D) = E_{t\sim p_{data}}[logD(t)] + E_{m\sim p_m(m))}[log(1 - D(G(m)))], \tag{4}$$

where $D(t)$ represents the probability that t came from the data rather than p_g, and p_{data} is the distribution of the real-world data. The model is considered to be stable when both reach the point where none of them can be improved, as $p_g = p_{data}$. That is, the discriminator can no longer identify between the two distributions. Figure 2(c) shows a GAN architecture.

Another famous generative model is VAE [81]. An example VAE architecture is given in Figure 2(d). It utilizes the log-likelihood of the data and leverages the strategy of deriving a lower bound estimator from the directed graphical models with continuous latent variables. The generative parameters θ in the generative model assist the learning process of the variational parameters ϕ in the variational approximation model. The Auto-Encoding Variational Bayes (AEVB) algorithm optimizes the parameters ϕ and θ for the probabilities encoder $q_\phi(z|x)$ in the neural network, which is an approximation to the generative model $p_\theta(x, z)$, where z is the latent variable under a simple distribution, i.e., $N(0, I)$, and I is the identity matrix. It aims to maximize the probability of each x in the training set under the entire generative process:

$$p_\theta(x) = \int p_\theta(z)p_\theta(x|z)dz. \tag{5}$$

3 DEEP LEARNING TECHNIQUES AND FRAMEWORKS

Different deep learning algorithms help improve the learning performance, broaden the scopes of applications, and simplify the calculation process. However, the extremely long training time of the deep learning models remains a major problem for the researchers. Furthermore, the classification accuracy can be drastically enhanced by increasing the size of training data and model parameters. In order to accelerate the deep learning processing, several advanced techniques are proposed in the literature. Deep learning frameworks combine the implementation of modularized deep learning algorithms, optimization techniques, distribution techniques, and support to infrastructures. They are developed to simplify the implementation process and boost the system-level development and research. In this section, some of these representative techniques and frameworks are introduced.

3.1 Unsupervised and Transfer Learning

Contrary to the vast amount of work done in supervised deep learning, very few studies have addressed the unsupervised learning problem in deep learning. However, in recent years, the

benefit of learning reusable features using unsupervised techniques has shown promising results in different applications. In the last decade, the idea of having a self-taught learning framework has been widely discussed in the literature [88, 130, 140].

In recent few years, generative models such as GANs and VAEs have become dominant techniques for unsupervised deep learning. For instance, GANs are trained and reused as a fixed feature extractor for supervised tasks in [130]. This network is based on CNNs and has shown its supremacy as unsupervised learning in visual data analysis. In another work, a deep sparse Autoencoder is trained on a very large-scale image dataset to learn features [88]. This network generates a high-level feature extractor from unlabeled data, which can be used for face detection in an unsupervised manner. The generated features are also discriminative enough to detect other high-level objects like animal faces or human bodies. Bengio et al. [11] propose a generative stochastic network for unsupervised learning as an alternative to the maximum likelihood that is based on transition operators of Markov chain Monte Carlo.

In practice, very few people have the luxury of accessing very high-speed GPUs and powerful hardware to train a very deep network from scratch in a reasonable time. Therefore, pretraining a deep network (e.g., CNN) on large-scale datasets (e.g., ImageNet) is very common. This technique is also known as transfer learning [157], which can be done by using the pretrained networks as fixed feature extractors (especially for small new datasets) or fine-tuning the weights of the pretrained model (especially for large new datasets that are similar to the original one). In the latter, the model should continue the learning to fine-tune the weights of all or some of the high-level parts of the deep network. This approach can be considered as a semisupervised learning, in which the labeled data is insufficient to train a whole deep network.

3.2 Online Learning

Usually, the network topologies and architectures in deep learning are time static (i.e., they are predefined before the learning starts) and are also time invariant [90]. This restriction on time complexity poses a serious challenge when the data is streamed online. Online learning previously came into mainstream research [21], but only a modest advancement has been observed in online deep learning. Conventionally, DNNs are built upon the Stochastic Gradient Descent (SGD) approach in which the training samples are used individually to update the model parameters with a known label. The need is that rather than the sequential processing of each sample, the updates should be applied as batch processing. One approach was presented in [137] where the samples in each batch are treated as Independent and Identically Distributed (IID). The batch processing approach proportionally balances the computing resources and execution time.

Another challenge that stacks up on the issue of online learning is high-velocity data with time-varying distributions. This challenge represents the retail and banking data pipelines that hold tremendous business values. The current premise is that the data is largely close in time to safely assume piecewise stationarity, thus having a similar distribution. This assumption characterizes data with a certain degree of correlation and develops the models accordingly, as discussed in [19]. Unfortunately, these nonstationary data streams are not IID and are often longitudinal data streams. Moreover, online learning is often memory delimited, is harder to parallelize, and requires a linear learning rate on each input sample. Developing methods that are capable of online learning from non-IID data would be a big leap forward for big data deep learning.

3.3 Optimization Techniques in Deep Learning

Training a DNN is an optimization process, i.e., finding the parameters in the network that minimize the loss function. In practice, the SGD method [150] is a fundamental algorithm applied to deep learning, which iteratively adjusts the parameters based on the gradient for each training

sample. The computational complexity of SGD is lower than that of the original gradient descent method, in which the whole dataset is considered every time the parameters are updated.

In the learning process, the updating speed is controlled by the hyperparameter learning rate. Lower learning rates will eventually lead to an optimal state after a long time, while higher learning rates decay the loss faster but may cause fluctuations during the training [128]. In order to control the oscillation of SGD, the idea of using momentum is introduced. Inspired by Newton's first law of motion, this technique gets a faster convergence and a proper momentum that can improve the optimization results of SGD [150].

On the other hand, several techniques are proposed to determine the proper learning rate. Primitively, weight decay and learning rate decay are introduced to adjust the learning rate and accelerate the convergence. A weight decay works as a penalty coefficient in the cost function to avoid overfitting, and a learning rate decay can reduce the learning rate dynamically to improve the performance. Moreover, adapting the learning rate with respect to the gradient of the previous stages is found helpful to avoid the fluctuation. Adagrad [35] is the first adaptive algorithm successfully used in deep learning. It amplifies the learning rate for infrequently updated parameters and suppresses the learning rate for the frequently updated parameters by recording the accumulated squared gradients. Since the squared gradients are always positive, the learning rate of Adagrad can become extremely small and does not optimize the model anymore. To solve this issue, Adadelta [176] is proposed, where a decay fraction β_2 is introduced to limit the accumulation of the squared gradients as follows:

$$E[g^2]_t = \beta_2 E[g^2]_{t-1} + (1 - \beta_2) g_t^2, \tag{6}$$

where $E[g^2]_t$ is the accumulated squared gradient at stage t and g_t^2 is the squared gradient at stage t. Later, the Adadelta is further improved by introducing another decay fraction β_1 to record the accumulation of the gradients [80]. It is shown that Adam performs better in practice than the other algorithms with an adaptive learning rate. AdaMax is also proposed in the same paper as an extension of Adam, where the $l-2$ norm used in Adam is replaced by the $l-$ inf norm to achieve a stable algorithm. Adam can also incorporate with Nesterov Accelerated Gradient (NAG), called NAdam [34]. It shows better convergence speed in some cases.

3.4 Deep Learning in Distributed Systems

The efficiency of model training is limited to a single-machine system, and the distributed deep learning techniques have been developed to further accelerate the training process. There are two main approaches to train the model in a distributed system, namely, data parallelism and model parallelism. For data parallelism, the model is replicated to all the computational nodes and each model is trained with the assigned subset of data. After a certain period of time, the weight update needs to be synchronized among the nodes. Comparatively, for model parallelism, all the data is processed with one model where each node is responsible for the partial estimation of the parameters in the model.

Among data-parallel approaches, the most straightforward algorithm to combine results from the slave nodes is parameter averaging [108]. Let $W_{t,i}$ be the parameter in a neural network on node i at time t with N slave nodes used for training. At time t, the weight on the master node is W_t. Then, a copy of the current parameters is distributed to the slave nodes. After the updated parameters are sent back to the master node, the weight at time $t+1$ on the master node will be

$$W_{t+1} = \frac{1}{N} \sum_{i=1}^{N} W_{t+1,i}. \tag{7}$$

Parameter averaging would be identical to single-machine training if parameters are averaged after each minibatch and if each worker processes the same number of data copies. However, the network communication and synchronization costs can nullify the benefits of extra machines. Therefore, the averaging process is usually applied after a certain number of minibatches are fed to each slave node. The frequency of training and the model performance need to be balanced as required. A more popular approach for data parallelism uses SGD and is known as update-based data parallelism [149], where the updates of the learning rate decay and momentum are transferred. However, the synchronous weight update is not scalable for a larger cluster. The overhead of communication increases exponentially with respect to the number of nodes. Therefore, a parameter server framework is proposed by Google to process the training asynchronously [92]. Instead of waiting for the parameter to be updated on the master node, the asynchronous update allows each node to spend more time on computation. Meanwhile, the network communication cost can be significantly reduced by decentralization, i.e., transmitting the updates in peer-to-peer mode instead of master-slave mode.

On the other hand, a model parallelism approach splits the training step across multiple GPUs. In a straightforward model-parallel strategy, each GPU computes only a subset of the model. For example, for a model with two LSTM layers, the system with two GPUs can use each of them to calculate one LSTM layer. The advantage of the model-parallel strategy is that it makes training and prediction with massive deep neural networks possible [28]. For instance, the COTS HPC system trained a neural network with more than 11 billion parameters, which requires about 82GB of memory [24]. It is impossible to fit such a large model into one machine and therefore it needs to be partitioned using model-parallel strategies. However, since the model is partitioned across nodes, one drawback of model parallelism is that each node can only compute a subset of results [8] and synchronization is thus needed to get the full results. The synchronization loss and communication overhead of model-parallel strategies are more than those of data-parallel strategies since each node in the former must synchronize both gradients and parameter values on every update step. In other words, the scalability of model parallelism is inferior. To handle this issue, Google has proposed an automated device placement framework based on deep reinforcement learning to find the best scheme of the model partition and placement [110]. The framework takes the embedding representation of each operation, places the grouped operations to different devices, and shows a 60% performance improvement compared to the human experts.

Both data-parallel and model-parallel strategies have their own limitations. On one hand, if data parallelism has too many training modules, it has to decrease the learning rate to make the training procedure smooth. On the other hand, if model parallelism has too many segmentations, the output from the nodes will increase sharply and reduce the efficiency accordingly [168]. Generally speaking, the larger the dataset is, the more beneficial it is to have data parallelism. The larger the deep learning model is, the more suitable it is to have model parallelism. Besides, compared to data parallelism, it is hard to hide the communication needed for synchronization in model parallelism because only partial information is included in each node for the whole batch, though some advanced frameworks like TensorFlow[1] support asynchronous kernels to save the communication cost. Thus, it is necessary to wait till the synchronization step finishes before moving forward to the next layer since the activities are unable to be processed with only partial information. The two kinds of strategies can also be fused to a hybrid model as discussed in [168].

3.5 Deep Learning Frameworks

Table 2 lists a smattering of popular deep learning frameworks for architecture designs, such as Caffe [72], DeepLearning4j (DL4j) [143], Torch [25], Neon [69], Theano [5], MXNet [17], TensorFlow [1], and Microsoft Cognitive Toolkit (CNTK) [173]. In Table 2, the license, core

Table 2. The Comparison of Different Deep Learning Frameworks

Framework	License	Core Language	Interface Support	CNN & RNN Support	DBN Support
Caffe [72]	BSD	C++	Python & MATLAB	Yes	No
DL4j [143]	Apache 2.0	Java	Java, Scala, & Python	Yes	Yes
Torch [25]	BSD	C & Lua	C/C++, Lua, & Python	Yes	Yes
Neon [69]	Apache 2.0	Python	Python	Yes	Yes
Theano [5]	BSD	Python	Python	Yes	Yes
MXNet [17]	Apache 2.0	C++	C++, Python, R, Scala, Perl, Julia, etc.	Yes	Yes
TensorFlow [1]	Apache 2.0	C++ & Python	Python, C/C++, Java, & Go	Yes	Yes
CNTK [173]	MIT	C++	Python, C++, & BrainScript	Yes	No

language, supported interface language, and framework support of CNN, RNN, and DBN are also listed.

It can be observed from Table 2 that C++ is usually used for implementation of deep learning frameworks because it accelerates the speed of training. Since GPU is significantly helpful to speed up the matrix computation, most of the aforementioned frameworks also support GPU via the interface provided by CuDNN [18]. Meanwhile, Python has become the most common language for deep learning architecture design since it can make the programming more efficient and easier by simplifying the programming process. Also, distributed calculation becomes common in some recently released frameworks such as TensorFlow, MXNet, and CNTK. The goal is to further improve the calculation efficiency for deep learning. Moreover, TensorFlow also includes support for the customized deep learning Application-Specific Integrated Circuit (ASIC), called Tensor Processing Unit (TPU), to help increase the efficiency and decrease the power consumption.

Caffe, implemented by Berkeley Vision and Learning Center, is one of the most widely used frameworks [72]. It supports the most commonly used layers for both CNN and RNN but does not directly enable the use of DBN. Users of Caffe design their architecture by declaring the structure of a computation graph, such as convolutional layers. There are pretrained models available for a wide range of neural networks such as AlexNet [86], GoogleNet [151], and ResNet [58]. Furthermore, Caffe is a single-machine framework. In other words, it does not support multinode execution while the multi-GPU calculation is supported when there are external offerings like CaffeOnSpark by Yahoo that integrate Caffe with a big data engine like Spark.

DL4j is the most popular framework implemented in Java, developed and maintained by Skymind since 2014 [143]. Cooperating with Hadoop and Spark, DL4j is capable of distributed computation as well. However, this framework is reported to have a longer training time for similar architectures benchmarked with other frameworks [84].

Torch was first released in 2002 and extended its deep learning feature in 2011 [25]. Combined with Facebook's deep learning CUDA library (fbcunn) [160], Torch can operate model- and

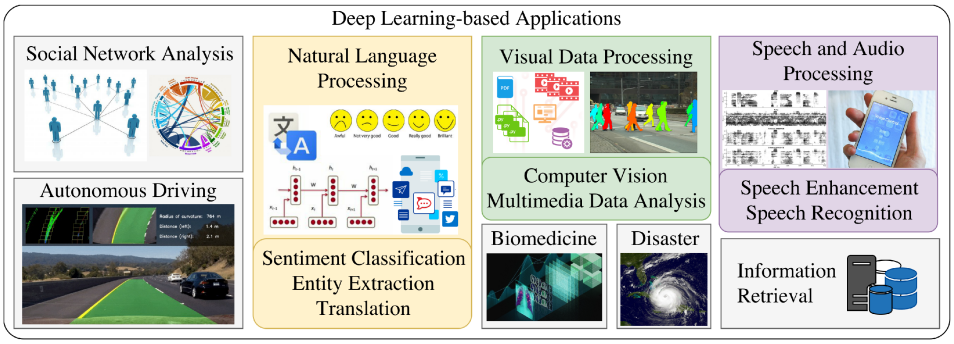


Fig. 3. Some of the popular deep learning applications.

data-level parallel computation. Unlike other frameworks, Torch is built based on a dynamic graph representation instead of a static graph. The dynamic graph allows the user to update the computational graph (i.e., to change the model structure) during runtime, while the static graph uses certain functions to define the graphs in advance. Recently, Torch released its Python interface, PyTorch, and the usage of this framework has greatly increased due to its flexibility.

Neon [69] and Theano [5] are two frameworks developed in Python by Intel and the University of Montreal, respectively. Both of them perform code optimizations in the system and kernel level. Therefore, their training speeds usually outperform other frameworks. However, although only parallelism and multi-GPU are supported, the multinode calculation is not designed in these frameworks.

MXNet supports several interfaces, including C++, Python, R, Scala, Perl, MATLAB, Javascript, Go, and Julia [17]. It supports both computation graph declarations and imperative computation declarations for architecture design. MXNet not only supports data and model parallelism but also follows parameter server schemes to support distributed calculation as well. MXNet has the most comprehensive functionality, but the performance is not optimized as much as other state-of-the-art frameworks.

TensorFlow is implemented by Google and provides a series of internal functions to help implement any deep neural network based on the static computational graph [1]. Recently, Keras started to support Tensorflow via a high-level interface and allowed users to design the architecture without worrying about the internal design. The framework provides different levels of parallel and distributed operations and well-designed fatal tolerance. The robustness of its design attracts a lot of users and it has become one of the most popular deep learning frameworks since its release.

CNTK, designed by Microsoft, has a specific high-level script language, BrainScript, for neural network implementation [173]. CNTK models the neural network as a directed graph. Each node in the graph represents an operation or a filter and each edge refers to the data flow. Instead of the parameter server model, the Message Passing Interface is applied for distributed calculation support.

4 VARIOUS APPLICATIONS OF DEEP LEARNING

Nowadays, applications of deep learning include but are not limited to NLP (e.g., sentence classification, translation, etc.), visual data processing (e.g., computer vision, multimedia data analysis, etc.), speech and audio processing (e.g., enhancement, recognition, etc.), social network analysis, and healthcare. This section provides details for the different techniques used for each application. Some of the main deep learning applications are also visualized in Figure 3.

Table 3. Popular Deep Learning Methods in NLP

Paper	NLP Tasks	Architecture	Datasets
Socher et al. 2013 [147]	Sentiment Analysis	RNTN	SST
Kim 2014 [79]	Sentiment Analysis, General Classification	CNN	SST
Wehrmann et al. 2017 [164]	Sentiment Analysis	Conv-Char-S	MTD
Bahdanau et al. 2014 [9]	Translation	Bidir RNN Encoder-Decoder	WMT-14-EF
Cho et al. 2014 [20]	Translation	RNN Encoder-Decoder	WMT-14-EF
Wu et al. 2016 [166]	Translation	GNMT	WMT-14-EF WMT-14-EG
Socher et al. 2011 [145]	Paraphrase Identification	Unfolding RAE	MSRP
Yin et al. 2015 [172]	Paraphrase Identification, Question & Answer	ABCNN	WikiQA MSRP
Kågebäck et al. 2014 [75]	Summarization	Unfolding RAE	OD
Dong et al. 2015 [33]	Question & Answer	MCCNN	WQ
Feng et al. 2015 [39]	Question & Answer	CNN	IQA

4.1 Natural Language Processing

NLP is a series of algorithms and techniques that mainly focus on teaching computers to understand the human language. Some NLP tasks include document classification, translation, paraphrase identification, text similarity, summarization, and question answering. NLP development is challenging due to the complexity and ambiguous structure of the human language. Moreover, natural language is highly context specific, where literal meanings change based on the form of words, sarcasm, and domain specificity. Deep learning methods have recently been able to demonstrate several successful attempts in achieving high accuracy in NLP tasks. Table 3 contains a summary for some of the leading deep learning NLP solutions, their architectures, and their datasets. Most NLP models follow a similar preprocessing step: (1) the input text is broken down into words through tokenization and then (2) these words are reproduced in the form of vectors, or n-grams. Representing words in a low dimension is important to create an accurate perception of similarities and differences between various words. The challenge arrives when there is a need to decide the length of words contained in each n-gram. This procedure is context specific and requires prior domain knowledge. Some of the highly impactful approaches in solving the most well-known NLP tasks are presented below.

4.1.1 Sentiment Analysis. This branch of NLP deals with examining a text and classifying the feeling or opinion of the writer. Most datasets for sentiment analysis are labeled as either positive or negative, and neutral phrases are removed by subjectivity classification methods. One popular example is the Standford Sentiment Treebank (SST) [147], a dataset of movie reviews labeled in five categories (ranging from very negative to very positive). Along with the introduction to SST, Socher et al. [147] propose a Recursive Neural Tensor Network (RNTN) that utilizes word vectors and parses a tree to represent a phrase, capturing the interactions between the elements with a tensor-based composition function. This recursive approach is advantageous when it comes to sentence-level classification since the grammar often displays a tree-like structure.

Kim [79] improves the accuracy for SST by following a different approach. Even though CNN models were first created with image recognition and classification in mind, their implementation in NLP has proven to be a success, achieving excellent results. Kim presents a simple CNN model using one convolution layer on top of trained word2vec vectors in a BoW architecture. The models were kept relatively simple with a small number of hyperparameters for tuning. By a combination of low tuning and pretrained task-specific parameters, they managed to achieve high accuracy on several benchmarks. Social media is a popular source of data when studying sentiments. The Multilingual Twitter Dataset (MTD) [114] is one of the largest public datasets, containing over 1.6 million manually annotated tweets in 13 languages. Applying sentiment analysis to tweets is challenging due to the short nature of the text. To address the issue of a multilingual dataset with a small amount of text, [164] proposes Conv-Char-S, a character-based architecture that is exempt from dependence on languages. Although the approach was not capable of outperforming word-embedding architectures, the authors argue its simplicity and predictive power consumption to be a good tradeoff.

4.1.2 Machine Translation. Deep learning has played an important role in the improvements of traditional automatic translation methods. Cho et al. [20] introduced a novel RNN-based encoding and decoding architecture to train the words in a Neural Machine Translation (NMT). The RNN Encoder-Decoder framework uses two RNNs: one maps an input sequence into fixed-length vectors, while the other RNN decodes the vector into the target symbols. The downside to the RNN Encoder-Decoder is the performance deterioration as the input sequence of symbols becomes larger. Bahdanau et al. [9] address this issue by introducing a dynamic-length vector and by jointly learning the align and translate procedures. Their approach is to perform a binary search to look for parts of speech that are most predictive for the translation. Nonetheless, the recently proposed translation systems are known to be computationally expensive and inefficient in handling sentences containing rare words. Thus, in [166], Google's Neural Machine Translation (GNMT) system is proposed, introducing a balance between the flexibility provided by character-level models and the efficiency of word-level models. GNMT is a deep LSTM network that makes use of eight encoder and eight decoder layers connected using the attention-based mechanism. The attention-based method was first introduced to improve NMT in general. The model achieved the state-of-the-art scores in WMT'14 English-to-French and English-to-German benchmarks.

4.1.3 Paraphrase Identification. Paraphrase identification is the process of analyzing two sentences and projecting how similar they are based on their underlying hidden semantics. It is a key feature that is beneficial for several NLP jobs such as plagiarism detection, answers to questions, context detection, summarization, and domain identification. Socher et al. [145] propose the use of unfolding Recursive Autoencoders (RAEs) to measure the similarity of two sentences. Using syntactic trees to develop the feature space, they measure both word- and phrase-level similarities. Even though it is very similar to RvNN, RAE is useful in unsupervised classification. Unlike RvNN, RAE computes a reconstruction error instead of a supervised score during the merging of two vectors into a compositional vector. The paper also introduced a dynamic pooling layer that can compare and classify two sentences of different sizes as either a paraphrase or not. Several other notable methods were investigated by [31] for monolingual phrase-level semantic similarity detection. They also enlist some of the most notable datasets in paraphrase identification, e.g., the Microsoft Research Paraphrase Corpus (MSRP) and the Topically Clustered News Article dataset. Attention-Based CNN (ABCNN) is a recently proposed deep learning architecture with the goal of determining the interdependence between two sentences [172]. Other than paraphrase detection, it has also been applied to answer selection and textual entailment.

4.1.4 Summarization. Automatic summarization can extract the most significant and relevant information from large text documents. A well-represented summary effectively reduces the size of text without losing the most important information. This can considerably decrease the time and computations required to analyze large text-based datasets. Kågebäck et al. [75] propose a continuous vector representation-based model for the sentences. Their model evaluates multiple combinations and compositions for meaningful representations. The new vector representation is tested using RAE compared with simple vector addition. The paper makes use of the ROUGE benchmarking metrics to evaluate the effectiveness of their summarization framework. Ganesan et al. [41] utilize a graph-based model that produces brief summaries from the opinion dataset known as Opinosis Dataset (OD). Their model targets user opinions in terms of feedback, product reviews, and customer satisfaction reports without losing any educative material.

4.1.5 Question Answering. An automatic question-and-answering system should be able to interpret a natural language question and use reasoning to return an appropriate reply. Modern knowledge bases, such as the famous FREEBASE dataset, allow this field to flourish and leap out of the times when features and rule sets were hand-crafted to specific domains. Dong et al. [33] came up with a multicolumn CNN approach that can analyze a question from several aspects, i.e., which context to choose, underlying semantic meaning of the answer, and how to form the answer. They use a multitasking approach that ranks the question-answer pairs and also simultaneously learns the correlations and affiliations of the low-level word semantics. A more general deep learning architecture that is not limited to any one language is proposed [39]. The Question Answering (QA) framework proposed by the paper is based on CNN and uses a corpus-based approach to answer questions in the insurance domain. They test many different setups of a CNN-based architecture and compare the results. Berant et al. [12] propose a highly scalable version of the question-answer model. Their solution to the problem of large datasets is to avoid the logical forms of text and learn the model solely on question-answer tuples. ABCNN [172] proves its capability in the Question-and-Answering NLP task by ranking the candidate answers based on how closely they were interdependent to the question. The datasets used by the papers mentioned in this section are Web Questions (WQ), Insurance Question Answering (IQA), and WikiQA.

4.2 Visual Data Processing

Deep learning techniques have become the main parts of various state-of-the-art multimedia systems and computer vision [54]. More specifically, CNNs have shown significant results in different real-world tasks, including image processing, object detection, and video processing. This section discusses more details about the most recent deep learning frameworks and algorithms proposed over the past few years for visual data processing.

4.2.1 Image Classification. In 1998, LeCun et al. presented the first version of LeNet-5 [91]. LeNet-5 is a conventional CNN that includes two convolutional layers along with a subsampling layer and finally ending with a full connection in the last layer. Although, since the early 2000s, LeNet-5 and other CNN techniques were greatly leveraged in different problems, including the segmentation, detection, and classification of images, they were almost forsaken by data mining and machine-learning research groups. More than one decade later, the CNN algorithm has started its prosperity in computer vision communities. Specifically, AlexNet [86] is considered the first CNN model that substantially improved the image classification results on a very large dataset (e.g., ImageNet). It was the winner of the ILSVRC 2012 and improved on the best results from the previous years by almost 10% regarding the top five test error. To improve the efficiency and the speed of training, a GPU implementation of the CNN is utilized in this network. Data augmentation and dropout techniques are also used to substantially reduce the overfitting problem.

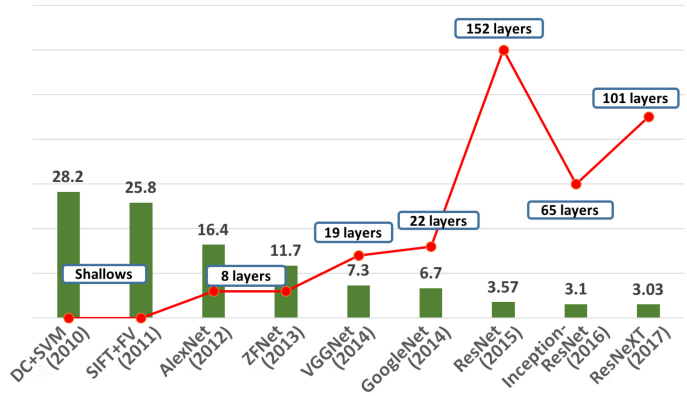


Fig. 4. The network top five errors (%) and layers in the ImageNet classification over time.

Since then, a variety of CNN methods have been developed and submitted to the ILSVRC competition. In 2014, two influential but different models were presented that mostly focused on the depth of neural networks. The first one, known as VGGNet [142], includes a very simple 19-layer CNN. In this network, at each layer, the spatial size of the input is reduced, while the depth of the network is increased to achieve a more effective and efficient model. Although VGGNet was not the winner of the ILSVRC 2014, it still shows a significant improvement (7.3% top five error) over the previous top models that came from its two major specifications: simplicity and depth. In contrast to VGGNet, GoogleNet [151], the winner of this competition (6.7% error), proposed a new complex module named "Inception," allowing several operations (pooling, convolutional, etc.) to work in parallel.

The Microsoft deep residual network (known as ResNet) [58] took the lead in the 2015 competitions including ILSVRC 2015 and in COCO detection and segmentation tasks by introducing the residual connections in CNNs and designing an ultra-deep learning model (50 to 152 layers). This model achieved an incredible performance (3.6% top five error), which means, for the first time, a computer model could beat human brains (with 5% to 10% error) in image classification. Contrary to the extremely deep representation of ResNet, it can handle the vanishing gradients [46] as well as the degradation problem (saturated accuracy) in deep networks by utilizing residual blocks.

In the last few years, several variations of ResNet have been proposed. The first group of methods has tried to increase the number of layers more and more. Current CNN models may include more than 1,000 layers [64]. Finally, in 2017, ResNeXT [167] was proposed as an extension of ResNet and VGGNet. This simple model includes several branches in a residual block, each performing a transformation that is finally aggregated by a summation operation. This general model can be further reshaped by other techniques such as AlexNet. ResNeXT outperforms its original version (ResNet) using half of the layers and also improves the Inception-v3 as well as Inception-ResNet networks on the ImageNet dataset. Figure 4 demonstrates the revolution of depth and performance in image classification (e.g., ImageNet) over time. The problem of supervised image classification is regarded as "solved" and the ImageNet classification challenge concluded in 2017.

4.2.2 Object Detection and Semantic Segmentation. Deep learning techniques play a major role in the advancement of object detection in recent years. Before that, the best object detection performance came from complex systems with several low-level features (e.g., SIFT, HOG, etc.) and high-level contexts. However, with the advent of new deep learning techniques, object detection has also reached a new stage of advancement. These advances are driven by successful methods such as region proposal and Region-based CNN (R-CNN) [45]. R-CNN bridges the

gap between the object detection and image classification by introducing region-based object localization methods using deep networks. In addition, transfer learning and pertaining on a large dataset (e.g., ImageNet) is utilized since the small object detection datasets (e.g., PASCAL [123]) include insufficient labeled data to train a large CNN network. However, in R-CNN, the training computational time and memory are very expensive, especially on new ultra-deep networks (e.g., VGGNet). Moreover, the object detection step is very slow. Later, this technique is extended to overcome the aforementioned issues by introducing two successful techniques: Fast R-CNN [44] and Faster R-CNN [133]. The former leverages sharing computation to speed up the original R-CNN and train a very deep VGGNet, while the latter proposes a Region Proposal Network (RPN) that enables almost real-time object detection.

A real-time object detection is called YOLO (You Only Look Once) [132], which contains a single CNN. The convolutional network performs bounding-box detection and class probability calculation for each box simultaneously. The benefits of YOLO include its fast training and testing (45 frames per second) and its reasonable performance compared to previous real-time systems.

Unlike Fast/Faster R-CNN, a recent method called Region-based Fully Convolutional Networks (R-FCNs) [95] utilizes a fully convolutional network that shares almost all computations on an image. This method uses the ResNet classifier as an object detector and achieves a test-time speed faster than the Faster R-CNN method. Finally, the Single-Shot MultiBox Detector (SSD) [100] is proposed, which is faster than YOLO, and its performance is as accurate as region-based techniques such as Faster R-CNN. Its model is based on a single CNN that generates a set of bounding boxes with fixed sizes as well as the corresponding object scores in the boxes.

Semantic segmentation is the process of understanding an image in pixel level that is necessary for real-world applications such as autonomous driving, robot vision, and medical systems. Now the question is how to convert image classification to semantic segmentation. In recent years, many research studies apply deep learning techniques to classify an image pixel-wise. A deconvolutional network [122], for instance, includes deconvolution and unpooling modules to detect and classify the segmentation regions. In another work, a Fully Convolutional Network (FCN) [101] is proposed and utilizes networks such as AlexNet, VGGNet, and GoogleNet. Recently, Mask R-CNN was proposed by Facebook AI Research (FAIR) [57] for object instance segmentation. It extends Faster R-CNN by adding a new branch that generates the segmentation mask prediction for each region of interest at the same time that the bounding box and class label are generated. This simple and flexible model has shown great performance results in both COCO instance segmentation and object detection.

4.2.3 Video Processing. Video analytics has attracted considerable attention in the computer vision community and is considered as a challenging task since it includes both spatial and temporal information. In an early work, large-scale YouTube videos containing 487 sport classes are used to train a CNN model [77]. The model includes a multiresolution architecture that utilizes the local motion information in videos and includes context stream (for low-resolution image modeling) and fovea stream (for high-resolution image processing) modules to classify videos. An event detection from sport videos using deep learning is presented in [159]. In that work, both spatial and temporal information are encoded using CNNs and feature fusion via regularized Autoencoders. In recent years, a new technique called Recurrent Convolution Networks (RCNs) [32] was introduced for video processing. It applies CNNs on video frames for visual understanding and then feeds the frames to RNNs for analyzing temporal information in videos. A new RCN model proposed in [10] uses RNN on the intermediate layers of CNNs. In addition, a Gated Recurrent Unit is used to leverage the sparsity and locality in the RNN modules. This model is validated on the UCF-101 and YouTube2Text datasets.

Table 4. Popular Visual Datasets for Deep Learning

Dataset	Data Type	Num of Instances	Num of Classes	Ground Truth	Applications
ImageNet [68]	Images	14M	1,000	Yes	Image classification, object localization, object detection, etc.
CIFAR10/100 [22]	Images	60K	10/100	Yes	Image classification
Pascal VOC [123]	Images	46K	20	Yes	Image classification, object detection, semantic segmentation
Microsoft COCO [96]	Images	2M	80	Yes	Object detection, semantic segmentation
MNIST [112]	Images	70K	10	Yes	Handwritten digit, classification
YFCC100M [152]	Images Videos	100M	8M	Partially	Video and image, understanding
YouTube-8M [4]	Videos	8M	4,716	Automatic	Video classification
Trecvid [158]	Videos	Varies	Varies	Partially	Video search, event detection, localization, etc.
UCF-101 [148]	Videos	13K	101	Yes	Human action detection
Kinetics [78]	Videos	306K	400	Yes	Human action detection

Three-dimensional CNN (C3D) [156] has demonstrated a better performance on video analysis tasks over the traditional 2D CNNs. It automatically learns spatiotemporal features from video inputs and models the appearance and motions at the same time. Two-stream networks [38] are another set of video analysis techniques that model spatial (RGB frame) and temporal information (optical flow) separately and average the predictions in the last few layers of the network. This network is extended in a recent work called Inflated 3D ConvNet (I3D), utilizing the idea of C3D. It is also pretrained on the Kinetics dataset [78]. The proposed approach could significantly enhance the performance of action recognition in UCF-101 and HMDB-51 datasets.

4.2.4 Visual Datasets. The significant advancements in image and video processing not only rely on the development of new learning algorithms and utilization of powerful hardware but also crucially depend on very large-scale public datasets. Several large-scale visual datasets used to train deep learning algorithms are listed in Table 4. ImageNet [68] can be considered as the most important and influential dataset in deep learning. It is used to train all popular networks such as AlexNet, GoogleNet, VGGNet, and ResNet due to its large-scale labeled image collections. A smaller-scale image dataset that is utilized in many research studies is CIFAR10/100 [22]. This dataset is also used for evaluating many DNNs in the image classification task. As mentioned earlier, PASCAL VOC and Microsoft COCO are used for various object detection and semantic segmentation tasks. Finally, YouTube-8M [4] is a relatively new dataset generated by Google to play the same role as ImageNet for video processing. It can be utilized as a benchmark dataset for various video analyses, including event detection, understanding, and classification.

4.3 Speech and Audio Processing

Audio processing is the process that operates directly on electrical or analog audio signals. It is necessary for speech recognition (or speech transcription), speech enhancement, phone classification,

and music classification. Speech processing is an active research area because of its importance in perfect human-computer interaction. From the 1970s till the 21st century, Automatic Speech Recognition (ASR) [74] technology has risen to an unprecedented level. However, it is still far from mimicking human-like behavior to communicate with human beings. An ASR system is made up of many components, including speech signal preprocessing, feature extraction, acoustic modeling, phonetic unit recognition, and language modeling. The traditional ASR systems integrate the Hidden Markov Models (HMMs) with the Gaussian Mixture Models (GMMs). The HMMs are used to deal with the variation of speech, which is related to the time space, while the GMMs represent the acoustic characteristics of sound units. The modeling process is time-consuming and requires a very large training dataset in order to reach a high accuracy. The ANNs [60] were introduced during the 1980s, which are composed of many nonlinear computational elements operating in parallel. However, deeper architectures with multiple layers are needed to settle the limitation of GMMs on sufficiently representing HMMs. DBN, one of the commonly used deep learning models in this area, significantly improves the performance of the acoustic models. It models the spectral variations in speech with RBMs as their building blocks. Seide et al. [139] use pretrained DBNs and demonstrate the strength of their model on a publicly available benchmark, the Switchboard phone-call transcription task. They introduce weight sparseness and the related learning strategy to reduce the recognition error and model size. Followed by the widely studied DBN pretraining method, Dahl et al. [26] propose a novel acoustic model for Large-Vocabulary-Speech-Recognition (LVSR). The model integrates a pretrained DNN using a DBN pretraining algorithm and a Context-Dependent (CD) hidden Markov model named CD-DNN-HMM. They use the unsupervised DBN as the pretraining algorithm to activate the training process. Instead of the phoneme benchmark, the evaluation was performed on LVSR. It was the first application that applied to a large vocabulary dataset with a pretrained DNN model. Many research studies follow this direction to investigate the further improvement and evaluate the efficiency.

Different from investigating the strength of DBNs, Graves et al. [51] focus on the exploration of deep RNNs, which achieves a testing error of 17.7% on the TIMIT phoneme dataset [42]. The deep LSTM performs better at recognizing long-range context using purpose-built memory cells to store the information. In recent years, the interests in speech recognition are not restricted to the improvement of an acoustic model within the ASR system. In [6], a large RNN (including uni- or bidirectional layers) with multiple convolutional layers was trained end to end using the Connectionist Temporal Classification (CTC) loss function. The proposed deep RNN architecture, called Deep Speech 2, takes advantage of the capacity provided by the deep learning systems and keeps the robustness of the overall network in a noisy environment. Besides, the approach has shown the capability of quickly applying to new languages with high-performing recognizers. The scalability of the model deployment on a GPU server is also evaluated and the model achieves higher efficiency with a low-latency transcription.

A CNN-RNN hybrid model, RCNN, is introduced in [180], which works for LVSR. Originally, CNNs were introduced into ASR to alleviate the computational problem. However, they tend to be very challenging to train and slow to converge. The core module inside RCNN is the Recurrent Convolutional Layer (RCL), whose state evolves over discrete time steps. The comparison is made with the LSTM on the TIMIT phoneme dataset.

Besides speech recognition tasks, many research studies focus on Speech Emotion Recognition (SER) [36], Speech Enhancement (SE), and Seaker Separation (SS), with the most current approaches summarized in Table 5.

4.3.1 Speech Emotion Recognition (SER). Emotions influence both the voice characteristics and linguistic content of speech. SER relies heavily on the effectiveness of the speech features used

Table 5. Popular Deep Learning Approaches in Audio Processing

Paper	Tasks	Architecture	Datasets
Abel and Tim 2017 [3]	SE	Regression-based DNN	TIMIT & SDC & NTT
Han et al. 2014 [56]	SER	ELM	IEMOCAP
Huang et al. 2014 [66]	SE	DNN and RNN	TIMIT
Kolbæk et al. 2017 [82]	SE	DNN	-
Neumann and Vu 2017 [118]	SER	Attentive CNN	IEMOCAP
Pascual et al. 2017 [125]	SE	GAN	Voice Bank corpus
Weng et al. 2015 [165]	SS	DNN	BRIR
Yu et al. 2017 [174]	SS	DNN and CNN	WSJ0-2mix & Danish-2mix
Zhang and Wang 2017 [178]	SS	DNN	2006 Speech Separation Challenge data

for classification and can be classified into two types: (1) global models for High-level Statistical Functions (HSFs) (e.g., mean, variance, median, linear regression coefficients, etc.) and (2) dynamic modeling approaches for frame-based dynamic Low-Level Descriptors (LLDs) like Mel Frequency Cepstral Coefficient (MFCC), voicing probability, harmonics-to-noise ratio, and so forth.

In [56], a newly developed ANN with one hidden layer, called the Extreme Learning Machine (ELM), is proposed for the utterance-level classification using DNNs. The method is evaluated using the audio track of the Interactive Emotional Dyadic Motion Capture (IEMOCAP) database, which contains audiovisual data from 10 actors. The experimental results demonstrate that the ELM's performance is enhanced compared to both HMM- and SVM-based approaches.

Besides showing the strength of the attentive CNN model on feature learning, CNN is also utilized for speech emotion recognition in [118]. That work achieves state-of-the-art performance results on the improvised IEMOCAP data.

4.3.2 Speech Enhancement (SE). Recently, speech enhancement has aimed to improve the speech quality by using the deep learning algorithm. In [3], a regression-based DNN Artificial speech Bandwidth Extension (ABE) framework is proposed to deal with speech enhancement tasks with narrowband speech signal inputs. The TIMIT database and the Speechdat-Car US (SDC) database are used for training of the DNN model. With pretrained sigmoid units, the improvements were achieved on the NTT database by more than 1.18dB of the upper band cepstral distance, and 0.23 MOS points improved compared to the HMM/GMM baseline.

Huang et al. [66] study the monaural source separation in deep learning. In their study, a joint optimization of the DNNs and RNNs with an extra masking layer is proposed and the performance evaluation is compared to the Nonnegative Matrix Factorization (NMF) models using the TIMIT speech corpus. Pascual et al. [125] also propose SEGAN, which leverages GAN for speech enhancement.

Speech Separation (SS) can be viewed as a subtask of speech enhancement, which aims to separate reverberant target speech from spatially diffuse background interference [178]. Different from a single-speaker environment, speaker separation focuses on reconstructing the speech of each speaker from a mixed speech with more than one speaker talking simultaneously. In the early stage, several methods, including soft mask, modulation frequency analysis, and sparse decomposition, have been proposed to address the issue of single-channel input. A DNN-based approach is proposed to attack the single-channel multitalker speech recognition problem in [165]. Their proposed approach showed remarkable noise robustness and outperformed the IBM superhuman system. In [174], the authors implement the speech separation model with the permutation-invariant training technique. The model includes feed-forward DNN with three hidden layers and one CNN

model to generate the separation view instead of multiclass regression or segmentation that was previously popular.

4.4 Other Applications

Other than all the aforementioned applications, deep learning algorithms are also applied to information retrieval, robotics, transportation prediction, autonomous driving, biomedicine, disaster management, and so forth. Please note that deep learning has shown its capability to be leveraged in various applications and only some of the selected applications are introduced in this section.

4.4.1 Social Network Analysis. The popularity of many social networks like Facebook and Twitter has enabled users to share a large amount of information including their pictures, thoughts, and opinions. Due to the fact that deep learning has shown promising performance on visual data and NLP, different deep learning approaches have been adopted for social network analysis, including semantic evaluation [116, 161, 179], link prediction [99, 163], and crisis response [120].

Semantic evaluation is an important field in social network analysis, which aims to help machines understand the semantic meaning of posts in social networks. Although a variety of techniques have been proposed to analyze texts in NLP, these approaches may fail to address several main challenges in social network analysis, such as spelling errors, abbreviations, special characters, and informal languages [161].

Twitter can be considered as the most commonly used source of sentiment classification for social network analysis. In general, sentiment analysis aims to determine the attitude of reviewers. For this purpose, SemEval has provided a benchmark dataset based on Twitter and run the sentiment classification task since 2013 [116]. Another similar example is Amazon, which started as an online bookstore and is now the world's largest online retailer. With an abundance of purchase transactions, a vast amount of reviews are created by the customers, making the Amazon dataset a great source for large-scale sentiment classification [179].

In the field of social networks, link prediction is also commonly used for many scenarios, such as recommendation, network completion, and social ties prediction. Deep-learning-based approaches are applied to improve the performance of the prediction and to tackle problems such as scalability and nonlinearity [163]. Since the data in social networks is highly dynamic, the conventional deep learning algorithm has been modified to adapt this characteristic. Most of the deep learning approaches use an RBM to perform link prediction since the unknown links between users can be directly modeled as the hidden layers in an RBM and thus be predicted. Liu et al. propose a supervised DBN approach based on the pretrained RBMs for link prediction [99]. In their approach, the process is separated into three steps and a pretrained RBM-based DBN is constructed for each part, where two layers of RMBs are contained in each DBN. The first step is unsupervised link prediction, where the encoded links are used as the input feature to generate the predicted link in an unsupervised manner. Next, the representations of the original links will be generated based on the output of the unsupervised link prediction in the feature representation step, and then the final step (i.e., link prediction step) is performed, where the link representations will generate the predicted links in a supervised way.

Different from the tasks of semantic classification and link prediction, crisis response in social networks requires the immediate detection of natural or man-made disasters. The main goals of crisis response are to identify informative pieces of posts and classify them into the corresponding topical classes like flood, earthquake, wildfire, and so forth. To address this topic, Nguyen et al. propose a CNN-based deep learning framework combined with the online learning feature to automatically detect the possible disasters by tweets at sentence level and identify the types of detected disasters [120]. The first goal is performed by a binary classification network, using

informative and noninformative pieces of posts as the labels. If it is informative, the posts will be further classified into a specific type.

4.4.2 Information Retrieval. Deep learning has a great impact on information retrieval. Deep-Structured Semantic Modeling (DSSM) is proposed for document retrieval and web search [65], where the latent semantic analysis is conducted by a DNN and the queries along with the click-through data are used to determine the results of the retrieval. The encoded queries and click-through data are mapped into 30k-dimension by word hashing and a 128-dimension feature space is generated by the multilayer nonlinear projections. The proposed DNN is trained to bridge the given queries to its semantic meaning with the help of the click-through data. However, this proposed model treats each word separately and ignores the connection between the words. A representative improved version of this method is Convolutional DSSM [141], where each word in the sequence is mapped to a 30k-dimension feature space. A convolutional structure is then integrated to generate several 300-dimension feature spaces for the subset of words in the sequence. At the end, a max-pooling layer and an additional projection layer are used to generate the final outputs. For a general information retrieval task, Deep Stacking Networks (DSNs) are proposed in [30]. An atomic module of the DSN is composed of simple classifiers or nonlinear functions. In each step, all the previous outputs of the module are stacked to the original input to generate the new results. Using this method, the original high-dimensional input features are represented by low-dimensional abstract features and thus the retrieval results can be improved.

4.4.3 Transportation Prediction. Transportation prediction is another application of deep learning. Ma et al. [105] propose a deep learning framework based on the RNN-RBM architecture to predict the transportation network congestion evolution due to the congestion in one location. The congestion status is encoded in a binary representation, and the historical data of transportation congestion is used as visible units (input sequence) of the model. The proposed method shows at least a 17.2% improvement in accuracy than the other approaches and takes around 3% of runtime. However, reasonable accuracy and efficiency are reached at the cost of losing the sensitivity and specificity of the model. Instead of the real-world traffic, Internet traffic, which is more complex due to its time-varying property, can be analyzed by the deep learning approach. A traffic matrix prediction and estimation method for a data center network is proposed based on the RBM-based DBN [121]. In the prediction module, a logistic regression model is contained in the output layer to generate the predicted traffic matrix value based on the model trained by the historical data. In the estimation module, the DBM model is trained by the prior link counts as the input and the traffic matrix at the same time as the output. Therefore, the current traffic matrix can be estimated by using the proposed model with link counts, which costs less computational time and resources. The deep learning approach shows at least improvements of 5.7% on prediction and 23.4% on estimation in comparison to most of the state-of-the-art approaches.

4.4.4 Autonomous Driving. A large number of big companies and unicorn startups including Google, Tesla, Aurora, and Uber are working on self-driving automotive technologies. Back in 2008, Hadsell et al. used a relatively simple DBN with two convolutional layers and one max subsampling layer to extract deep features [55]. They used a self-supervised learning technique to long-range vision in the off-road terrain by training a classifier to discriminate the feature vectors. Recently, autonomous driving systems were categorized into robotics approaches for recognizing driving-relevant objects and behavioral cloning approaches that learn a direct mapping from the sensory input to the driving action. The traditional robotics approaches involve recognition of driving-relevant objects and a combination of sensor fusion, object detection, image classification, path planning, and control theory. Geiger et al. built a rectified autonomous driving dataset that

captures a wide range of interesting scenarios including cars, pedestrians, traffic lanes, road signs, traffic lights, and so on [43].

The behavioral cloning approaches are often based on deep learning, which involves training DNNs to take the sensor inputs and then produce steering, throttle, and brake outputs. Koutník et al. trained fully connected large-scale RNNs using a vision-based reinforcement learning approach [83]. They also used compressed network encoding to reduce the dimensionality of the search space by utilizing the inherent regularity in the environment. To keep the car on the track, their networks map the image directly to the steering angles. A recent paper takes advantage of both approaches [15] by constructing a mapping from an image to several possible affordance indicators of the road situation, e.g., the distance to the lane markings, the angle of the car relative to the road, and the distance to the cars in the current and adjacent lanes. With such a compact affordance representation as the perception output, they build an automated CNN-based framework to learn deep learning features from the images for affordance estimation and then make high-level driving decisions. While the autonomous driving technology is now more mature, it still has a long way to go to handle unpredictable and complex situations.

4.4.5 Biomedicine. Deep learning is a highly progressive research field, but its reach in the domain of histopathology is an open opportunity. One of the early attempts includes the sensing of mitotic figures and determination/division of cells as proposed in [23]. Another method employed a CNN-based Autoencoder to section basal cell carcinoma in breast cancer [98]. The framework applies CNNs on the sentinel lymph nodes and tries to accurately detect all clumps of the isolated tumor cells. However, these methods lag generalizing on large datasets, which makes it harder to evaluate their real-world relevance. Moreover, several of the studied methods using CNNs train their models from a single patient care center or lab.

In the treatments of stroke, prostate cancer, and breast cancer, survival and risk prediction procedures are highly relevant. There is a huge gap of deep learning methods in this domain, with only a few notable papers concentrating on deep survival analysis [97]. Survival analysis is founded on structured attributes like patient age, marital status, and BMI, but the recent advancements in medical imaging provide unstructured images to also predict survival probabilities. Conventionally, the features were obtained by human design. However, researchers have challenged that these features provide limited insight in depicting highly conceptual data [87]. Deep learning models such as CNNs are perfectly suited to represent such conceptual attributes for survival analysis, and they can successfully outperform the existing Cox hazard-based state-of-the-art frameworks. Nonetheless, there are still limitations and challenges that require attention from the research community [131].

With the newest research progress in machine learning, more complicated biomedicine tasks can be accomplished by the deep learning techniques. The even more fascinating news is that the machines can now learn and reveal things undetectable by human beings. Recently, a research team from Google and Stanford [126] used deep learning to discover new knowledge from retinal fundus images. They can now predict cardiovascular risk factors not previously thought to be quantifiable or present in retinal images, i.e., beyond current human knowledge.

4.4.6 Disaster Management Systems. Another application is disaster management systems, which have attracted great attention in the machine-learning community. Disasters affect the community, human lives, and economy structures. A well-built disaster information system can help the general public and personnel in the Emergency Operations Center (EOC) to be aware of the current hazard situation and to assist in the disaster relief decision-making process [154]. Currently, the major challenge of applying the deep learning methods to disaster information systems is that the systems need to deal with the time-sensitive data and provide the most accurate assistance

in a nearly real-time manner. When an accident or natural catastrophe suddenly happens, a great amount of data needs to be collected and analyzed. Tian et al. [153] apply traditional neural networks to build a prototype of a multimedia-aided disaster information system. MLP is integrated with a feature translation algorithm to perform a multilayer learning structure. Though there are research studies that utilize deep learning in disaster information management [127, 129], it is still in its early stages and has great potential in deep learning.

5 DEEP LEARNING CHALLENGES AND FUTURE DIRECTIONS

With the acute development in deep learning and its research venues being in the limelight, deep learning has gained extraordinary momentum in speech, language, and visual detection systems. However, several domains are practically still untouched by DNNs due to either their challenging nature or the lack of data availability for the general public. This creates significant opportunities and fertile ground for rewarding future research avenues. In this section, these domains, key insights into their challenges, and likely future directions of major deep learning methods are discussed.

There is a lingering black-box perception of DNNs, meaning that deep learning models can be assessed based on their final outputs without the understanding of how they get to these decisions. This weak statistical interpretability has also been identified in [52], especially in applications where the data is produced not by any type of physical manifestation. Ma et al. explain neural networks using cell biology from the molecular scale up [104]. They mapped the layers of a neural network to the components of a yeast cell, starting with the microscopic nucleotides that make up its DNA, moving upward to larger structures such as ribosomes (which take instructions from the DNA and make proteins), and finally moving to organelles like the mitochondrion and nucleus (which runs the cell operations). Since it is a visible neural network, they could easily observe the changes in cellular mechanisms when the DNA was altered.

One unique technique by Google Brain peers into the synthetic brain of a DNN by a method called "inceptionism" [113]. It isolates specific parts of the data with each neuron's estimate about what it sees and the certainty of the neuron. This process is coupled with the deep dream technique to map the network's response to any given image [14]. For instance, with the images of cats and dogs, the relevant neurons are almost always pretty sure about the dog's floppy ears and the cat's pointy ears, which helps to dissect the datasets and interpret parts of the network. Manning et al. [106] also talk about similar methods to understand the semantics behind a given dataset by peeking into various network paths, as activated by parts of the data. However, there is a lack of attention to this problem, which is largely attributed to the different ways in which the statisticians and machine-learning professionals use deep learning [37]. The most plausible way forward is to relate the neural networks to the existing well-known physical or biological phenomenon. This will aid in developing a metaphysical relationship that can help demystify a DNN brain. Moreover, the consensus from the literature is that the deep learning researchers need to simplify their interfaces with low processing overheads so that the models can be analyzed for better understanding.

This leads us to the next challenge, that the most relevant future machine-learning problems will not have sufficient training samples with labels [90]. Apart from the zettabytes of currently available data, petabytes of data are added every day. This exponential growth is piling up data that can never be labeled with human assistance. The current sentiment is in favor of supervised learning, mostly because of the readily available labels and the small sizes of current datasets [53]. However, with the rapid increases in the size and complexity of data, unsupervised learning will be the dominant solution in the future [111]. Current deep learning models will also need to adapt to the rising issues such as data sparsity, missing data, and messy data in order to capture the approximated information through observations rather than training. Furthermore, incomplete,

heterogeneous, high-dimensional, unlabeled, and low-sample datasets are open venues for deep learning methods. This is very exciting because the inherent agnostic black-box nature of DNNs gives them the unique ability to work with the unsupervised data [59]. More and more advanced deep learning models are built to handle noisy and messy data [85]. The authors in [155] attempt to tackle the challenging database with 80 million tiny images that contains low-resolution RGB photos from 79,000 queries. They used a novel robust cost function to reduce the noisy labels in their data. Moreover, an increasing number of applications now involve huge amounts of data in a streaming live format, including time series, DNA/RNA sequencing, XML files, and social networks. All of these data stores suffer from incompleteness, heterogeneity, and unlabeled data. How deep learning models learn in these domains has been under discussion and is a relevant problem at this time [6].

Another landmark challenge faced by deep learning methods is the reduction of dimensionality without losing critical information needed for classification [119]. In medical applications like cancer RNA sequencing analysis, it is common that the number of samples in each label is far less than the number of features. In current deep learning models, this causes severe overfitting problems and inhibits proper classification of untrained cases [7]. Few methods try to empirically deduce variable predictability [13] and reduce the feature set in a supervised manner, but this often results in the loss of resolution and details. Similar challenges are faced when analyzing medical images because the training data is tremendously costly and time-consuming to obtain. A few foundational papers have attempted to build the models that require a minimal number of samples during learning [16, 98], where [23] stands out as a pioneer publication in applying CNNs to breast and prostate cancer detection.

A strong way forward is what is known as deep reinforcement learning [94]. The idea is inferred from behavioral psychology, where machine-learning agents take actions to minimize an aggregate cost. The methods use game theory, control theory, multiagent systems, and so forth and learn to perform actions where the given data is limited. In multimedia data, we start by feeding an image to the network and say, "Give me more of what you see." This generates a feedback loop: if a cloud looks similar to a rabbit, then the neural network will reinforce it to look more like a rabbit. After several iterations, the process will consequently make the network predict a rabbit more distinctly, till an elaborate bunny appears. The results are fascinating as even a relatively small network trained on a few tumor cells can be used to overinterpret an image and detect minute details that are currently undetected by deep learning.

One of the growing pains of deep learning relates to the issue of computational efficiency, i.e., achieving the maximum throughput while consuming the least amount of resources [103]. Current deep learning frameworks require considerable amounts of computational resources to approach the state-of-the-art performances [177]. One method attempts to overcome this challenge by using reservoir computing [71]. Another alternative is to use the incremental approaches that exploit medium and large datasets on offline training [109]. In current years, many researchers have shifted focus to build parallel and scalable deep learning frameworks [26, 60]. Lately, the focus has been shifted to migrate the learning process on GPUs. However, GPUs are notorious for their leakage currents, and this abstracts any plausible realization of the deep learning models on portable devices [63]. One solution is to use Field-Programmable Gate Arrays (FPGAs) as deep learning accelerators in order to optimize the data access pipelines to achieve significantly better results [175]. Wang et al. [162] use a Deep Learning Accelerator Unit (DLAU) as a scalable architecture that uses three pipelined processing units. They use the tile methods and locality techniques to attain up to a 36.1 times increase in speed compared to CPUs with 234mW power consumption. Another approach targets an architecture based on low-end FPGAs with arc losses, leakages, and so forth and still manages to achieve a 97% detection rate [117]. They were able to

achieve 7.5 times faster processing speed than a software implementation. Although GPUs provide peak floating-point performance, FPGAs require less power for similar performance throughput, and they can be mounted on a motherboard. A unique approach is proposed by [177] to implement CNNs using a roofline model. Since memory bandwidth in the FPGA design is critical, they evaluate the required memory bandwidth using loop tiling. Their implementation achieved 61.62 gigaflops under 100MHz, which significantly reduces the power consumption, where gigaflops are a unit of measuring the performance of a floating-point unit processor. Unfortunately, there are no deep learning FPGA test beds available at this time, which limits the exploration of this area to only those who are well versed with the FPGA design.

6 SUMMARY

Deep learning, a new and hot topic in machine learning, can be defined as a cascade of layers performing nonlinear processing to learn multiple levels of data representations. For decades, machine-learning researchers have tried to discover the patterns and data representations from the raw data. This method is called representation learning. Unlike conventional machine-learning and data mining techniques, deep learning is able to generate very high-level data representations from massive volumes of raw data. Therefore, it has provided a solution to many real-world applications.

This article surveys the state-of-the-art algorithms and techniques in deep learning. It starts with a history of artificial neural networks since 1940 and moves to recent deep learning algorithms and major breakthroughs in different applications. Then, the key algorithms and frameworks in this area, as well as popular techniques in deep learning, are presented. It first briefly introduces the traditional neural networks and several supervised deep learning algorithms, including recurrent, recursive, and convolutional neural networks, as well as the deep belief networks and Boltzmann machines. Thereafter, more advanced deep learning approaches such as unsupervised and online learning are discussed. Moreover, several optimization techniques have also been provided. Popular frameworks in this area include TensorFlow, Caffe, and Theano. In addition, to handle big data challenges, the distributed techniques in deep learning are briefly discussed. Thereafter, this article reviews the most successful deep learning methods in various applications, including NLP, visual data processing, speech and audio processing, and social network analysis.

This article discusses the challenges and provides several existing solutions to these challenges. However, there are still several issues that need to be addressed in the future of deep learning. Several findings of this article and possible future work are summarized below:

- Although deep learning can memorize a massive amount of data and information, its weak reasoning and understanding of the data makes it a black-box solution for many applications. The interpretability of deep learning should be investigated in the future.
- Deep learning still has difficulty in modeling multiple complex data modalities at the same time. Multimodal deep learning is another popular direction in recent deep learning research.
- Unlike human brains, deep learning needs extensive datasets (preferably labeled data) for training the machine and predicting the unseen data. This problem becomes more daunting when the available datasets are small (e.g., healthcare data) or when the data needs to be processed in real time. One-shot learning and zero-shot learning have been studied in the recent few years to alleviate this problem.
- The majority of the existing deep learning implementations are supervised algorithms, while machine learning is gradually shifting to unsupervised and semisupervised learning to handle real-world data without manual human labels.

- In spite of all the deep learning advancements in recent years, many applications are still untouched by deep learning or are in the early stages of leveraging the deep learning techniques (e.g., disaster information management, finance, or medical data analytics).

All in all, deep learning, a new and fast-growing method, provides numerous challenges as well as opportunities and solutions in a variety of applications. More importantly, it transfers machine learning to its new stage, namely, the "Smarter AI."

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