

Deep Learning Driven Networking Applications

V. R. Rashmi¹, H. D. Phaneendra²

¹Student, Department of Computer Science and Engineering, National Institute of Engineering, Mysore, India

²Professor, Department of Computer Science and Engineering, National Institute of Engineering, Mysore, India

Abstract: Deep learning architectures are inspired from the architecture of human brains since brains also have a deep architecture. With the progress and advancement of the Internet, networking research has become one of the most important fields. Since the networking deals with difficult problems that require effectual results, deep learning algorithms work very well in network domain by leveraging their capabilities for advanced network performance. Though, many researchers have exploited deep learning in networking but have been found to be dispersed in the literature. The present research has been focused on to contribute to the limited literature on applications of deep learning in computer networking. This research has focused on deep learning researches in the network related areas such as network traffic classification, WSN and social networks, network flow prediction and mobility prediction. The present research will facilitate the readers to find some motivating and stimulating research areas to pursue in the significant field of deep learning in networking domain and move ahead in the forward direction.

Keywords: Deep learning, Computer networking, Machine Learning, Architectures.

1. Introduction

Deep learning can be defined as “a branch of ML based on a set of algorithms, which construct computational models aiming to represent high-level data abstractions” [1]. Deep learning architectures are inspired from the architecture of human brains since brains also have a deep architecture [2]. Deep learning comes into picture when computers imitate similar deep architectures. As human brains work by firstly understanding the simpler concepts and build on them to work on complex concepts. Similarly, researchers train the computers at many levels of abstraction and processing to deal with computational problems. Depending on the use, deep architectures are classified as –

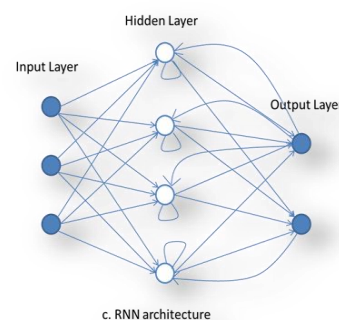
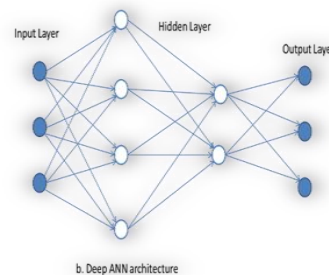
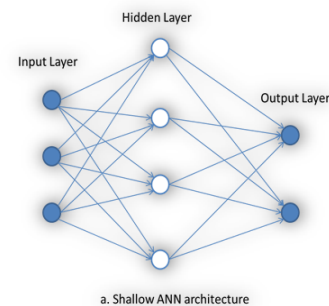
- *Generative Architecture* – For synthesis purposes, it uses high-order correlation characteristics of the input data
- *Discriminative Architecture*- It is used for used for recognition uses or pattern classification
- *Hybrid Architecture*- It is a mixture of generative and discriminative architecture

Some of the important deep learning models are presented as below,

- **Shallow Artificial Neural Network (ANN)** - The learning units (neurons) (Fig.1 a) of the hidden layer are linked in a completely interconnected way with neurons of the previous layer. Every neuron receiving numerous inputs

takes their weighted sum, sends it through an activation function. After this, an output is presented in form of a response.

- **Deep ANN**- It has more than one hidden layer of neurons which process the inputs (Fig.1 b).
- **Recurrent Neural Networks (RNNs)** - It possess a deep generative architecture [3]. The depth of this architecture is dependent on the length of the input sequence (Fig. 1 c)
- **Auto Encoder**- It is an ANN focused on to learn efficient coding [4] by encrypting a set of data (Fig. 1 d).



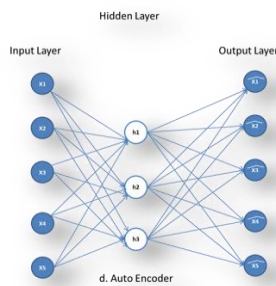


Fig. 1. Deep Learning Architectures

A. Computer Networking and Deep Learning-The Present Scenario

With the progress and advancement of the Internet, networking research has become one of the most important fields. Researchers and network operators deal with different types of networks like wired or wireless networks. Then there are different applications as well like live streaming or network security. Further, different network applications have their own characteristics and performance requirements which are very dynamic in nature. Because of the variety and complications of networks, definite algorithms are to be built for different demands of the user and the characteristics of the network. Since the networking deal with difficult problems that require effectual results, deep learning algorithms work very well in network domain by leveraging their capabilities for advanced network performance. The reasons for importance of deep learning in networking are as follows,

- The classification and prediction properties of deep learning facilitate in dealing with networking issues like prediction of performance and intrusion detection [5].
- Deep learning facilitates in decisions making which then helps in network scheduling [6] and parameter adaptation [7], [8].
- Many network problems require building analytic models to embody multifaceted system behaviours like throughput characteristics [5] or load changing patterns of content delivery network [9]. Deep learning helps in creation of an estimated model for these systems with adequate precision.
- Deep learning can deliver new options to build the generalized model using a uniform training method for dealing with different characteristics of networking scenarios like network states and traffic patterns [7], [8].

B. Association of Deep Learning with Computer Networks-The Research Gap

The deep learning applications can be seen to be researched in various topics in computer science. When it comes to networking domain, the use of deep learning for providing solutions to different complexities of communication networks

have not been formally studied in the existing literature. Though, many researchers have exploited deep learning in networking but have been found to be dispersed in the literature. The implication of using deep learning for computer networks can create a new inter-disciplinary research area. Thus, the present research has been focused to present deep learning applications in a single research to get all-inclusive attention from the network researcher and enrich the existing literature on deep learning applications in computer networking.

2. Applications of deep learning in areas of computer networking

A. Wireless Sensor Networks Statistical analysis and Deep Learning

Wireless Sensor Networks (WSNs) [10]–[14] have been known to use numerous applications of deep learning [15]. Neural networks, decision trees and reinforcement learning, have been prevalent algorithms applied in WSN. It mainly consists of WSNs which involve of many independent, small, low-cost and low power sensor nodes to gather different information. For example, supervised learning methods to report objects targeting and localization in WSNs have been widely used in the researches. The noticeable deep learning researches in the Medium Access Control layer of the WSN for intelligent scheduling has been conducted by different researches in the existing literature. Further, WSN security aspects like intrusion detection has been considered using Machine Intelligence theory in [16]. Other research areas of WSN like query processing and event detection [17], and Quality of service fault detection and data integrity have also used deep learning aspects. Also, K-Nearest Neighbor (K-NN) was applied widely in the WSNs specifically for the query processing [17].

B. Deep Learning in Network Traffic Classification

Network traffic control system’s traffic classification has been found to be constantly using deep learning [18], [19]. Deep learning techniques are expected to perform network traffic classification used in Quality of service, network monitoring, intrusion-detection, and many other used in different network settings [20]. Further supervised deep learning techniques have been used to label different network traffic traces with earlier known uses in [21], [22]. Unsupervised deep learning techniques were researched in different researches in last decade. The researchers presented automatic network traffic classification via traffic features, like packet-size, period between packets arrival, recurring traffic patterns, and many others. Work on different classifiers like decision trees, naive Bayes and neural networks have been studied in many previous works. The research conducted in [20] focused on a traffic classification engine in the Software Defined Networks edge switches. It further presented a “global” traffic classification using the network controller. After a huge amount of data on network traffic flows and their respective

labels are accessible, the issue of protocol classification was presented to be cracked by deep neural networks [23] along with stacked Auto-Encoders.

C. Prediction of Network Flow with Deep Learning

A network traffic flow is defined as “a sequence of data packets, which share the same context between source-destination pairs that include Transport Control Protocol (TCP) connections, media stream, and so forth” [1]. For managing the limited networking resources, data on the flow features like the inter-burst gap and burst size are often taken into consideration. In the case of Software Defined Networks, the flow information facilitates in programming routers, scheduling clogged data traffic, mitigating wireless interferences, and many more. Among traditional deep learning, studies on an extensive variety of time-series models for the Internet data traffic have been conducted. For dispersal of movement from the packet sampling conducted at the routers, researchers have presented ways to estimate the actual packet-size. Further, many researches presented a technique to get the frequencies (original) of flow lengths from a sparse packet sampling. This research was comparable with the face recognition system presented in [23] for conducting classification using a sparse demonstration of characteristics. Alike demonstration of characteristics-based pooling to build advanced level features for traffic flows predicting were researched in different previous researches.

D. Deep Learning in Social Networks

Social networking [24] has become an important research topic since past 4G mobile networks carry on to develop, taking deep learning applications into use [25]. Social networking based on the interaction of users, forecasting and anticipating their behavior toward a different service, application, preference, location, and many more is significant for the network operators. E-commerce sites, advertisement display networks, online marketing, and similar aspects use this data of the social network to increase their effectiveness. The varying arrangements demonstrated by users of social network involve time spent on each application, frequency, search, repetitive visits, and many more [26]. These patterns are used by deep learning to measure their search behavior. The research in [27] took into consideration a probabilistic generative process to design purchase and exploratory history of the user. Machine learning techniques like boosted decision trees and logistic regression which were used in prediction of patterns in social networking are now being replaced deep learning. The deep neural are more effective and efficient when compared with conventional machine learning techniques. This is because of the ability of deep learning to find the non-linear relationship in the social network users. Also, the deep learning consists of better modeling capabilities than machine learning [27].

E. Deep Learning in Social Networks

Mobility prediction is an important aspect for determination

of resource allocation, capacity estimation, and many other [27]–[30]. The research of [31] focused on predicting mobility of human as an important requirement for broad-domain applications including sending dinner coupons to widespread control and meek home preheating [32], [33], prediction of traffic [34], [35], urban planning [36]–[38], management of resource for mobile communications [39]–[41]. To provide suitable services to timely mobile users, paths prediction and time-resolved places mobility was proposed. Using deep learning methods, mobility prediction is expected to make the entire process of mobility prediction even better [42]. [43] presented a mobility prediction by using fully-complex extreme learning machines. These deep learning structures are based on fully-complex activation functions known as CELMs. CELMs can work without the requirement to adjust the factors of the connections between the inputs to hidden layers. Further, [44] created a deep Recurrent Neural Network to forecast human mobility in urban settings.

3. Conclusion

Deep learning is a branch of Machine learning that holds immense potential in the field of networking. It has even more significance since it is superior to machine learning when comes to efficiency and performance. The deep learning has just started to find applications in network systems. The researcher has identified this as a research gap. Owing to this, the present research has been focused on to contribute to the limited literature on applications of deep learning in computer networking. In the beginning of the paper, the author presented the importance of deep learning in the field of networking. Prior to this, the author discussed the applications of deep learning researches in the network related areas such as network traffic classification, WSN and social networks, network flow prediction and mobility prediction. The present research has been presented as a base for understanding the concepts of deep learning and its implementation in networking. This paper will facilitate the readers to find some motivating and stimulating research areas to pursue in this significant field and move ahead in the forward direction by selecting one of the application areas for further research.

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