

Applications of Deep Learning: A Review

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Abstract: Deep learning is a field of artificial intelligence that is based on the working of the human brain in data processing and pattern generation for decision-making purposes. This paper studies the applications of deep learning techniques in the prospect of different emerging areas. Deep learning based on artificial neural networks will be treated as a key tool for the functioning and modelling of future communication networks. The data-driven strategies, that enrich the traditional techniques based on mathematical paradigms, enable artificial neural networks to be integrated with future communication networks. This paper presents a detailed study of the applications of deep learning and also illustrates a case study where deep learning technique is applied to a dataset containing the biomechanical features of orthopaedic patients. The results show the accuracy levels in varying levels of inputs of hidden layer nodes.

Keywords: Deep learning, Applications, Artificial Intelligence, Artificial Neural Networks

1. INTRODUCTION

Deep Learning deals with the creation of neural networks consisting of more than two layers with the inclusion of appropriate weights and biases. The weights indicate the influence of the inputs in the output. These neural networks have the ability in approximating very complex functionalities. Deep learning signifies complex representations in terms of simple representations and this improves representation learning to a greater extent. Complex mappings are broken into simple and nested mappings and each simple mapping is represented as a layer of the neural network model. As represented in Figure 1.1, deep learning along with representation learning and machine learning are the subfields of Artificial Intelligence.

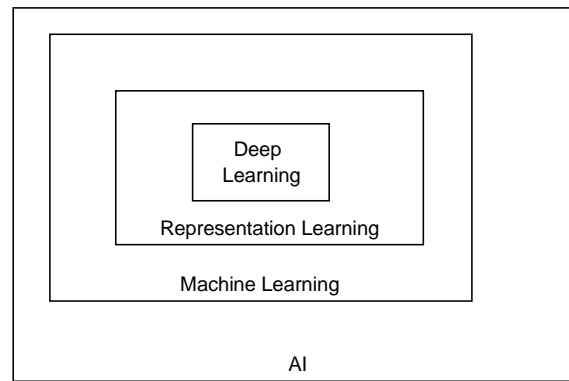


Figure 1.1: Deep learning as a subset of AI

Deep learning is a type of machine learning that attains greater flexibility by characterizing the real world as layers of concepts. Each concept is described as a collection of simpler concepts and each abstract illustration is calculated as a set of less abstract illustrations. The input layer of the neural network contains the observed characteristics of the real-world problem. The hidden layer values are decided based on the relationships observed in the input data. The output layer represents the data value that is predicted out of the given input values. The deep learning models are engineered on the perspective that is inspired by the human brain.

2. APPLICATIONS OF DEEP LEARNING

Deep learning finds its applications in a variety of domains and it has garnered attention from a wide group of researchers. Its uses help improve the performance and productivity of the applied domain. Studying the number of people in a specific area is an important process in quite many applications. This can be done by capturing images and videos from the area using computer vision and deep learning strategies. This process helps to manage energy in smart buildings and to build smart museums. It also helps in effectively managing people during the emergency period. The application also extends to managing power usage in common areas based on the presence of people [1]. Deep learning finds its applications as an important method in processing marine data. It is proved that deep learning models obtained better prediction accuracy. Deep belief networks are trained by an unsupervised learning method called contrastive divergence (CD). These networks can be used to perform classification and applied as a tool for dimensionality reduction. These networks can learn all features simultaneously in a single layer [2].

Deep learning can be used to build a classification of sports activities where the activities of different sets of people can be recognized precisely. As wearable smart technologies are rapidly becoming popular, the time consumption and error during the analysis of sports activities play a vital role. Many contributions in the machine learning field focused on the classification of activities based on inertial sensing. But there is not sufficient literature on the usage of neural networks to excerpt characteristics from available data to distinguish different sports actions [3]. Characterization of tumors from medical images can be performed accurately by applying deep learning algorithms and this enables customized treatment planning and efficient prognosis of the disease. The learning

algorithms can be used to address the limited availability of labeled data thereby obtaining substantial advantages [4].

One of the popular research problems in computer vision is scene recognition. The deep learning approaches not only learn shallow representations for scene recognition but also consider the structural information in images. These semantic modeling techniques based on deep learning show greater advantages than traditional imaging techniques [5]. A popular method to treat neurological disorders is to use deep brain stimulators that enable medical devices to be implanted in patients. Security in such devices is an important issue as a breach of security can cause a fake stimulation to the brain. Deep learning techniques can be used to identify the attacks in the brain stimulators and to distinguish between false and authentic stimulations [6].

A large group of users with mobile devices share data and extract information for analysis of any feature of interest is called crowd-sensing. As these mobile crowd-sensing systems must encounter security threats, deep learning methods can be used to improve data security by identifying fake sensing and intrusion detection [7]. Machine learning and its different variants can successfully be employed in analyzing biological data obtained from different sources like omics, bioimaging, gene expression, and medical imaging. Deep learning that is a part of machine learning gathers abstract characteristics from a large set of data without human intervention. The higher-level representations are learned from lower-level abstract representations. This process of learning hierarchically enables the system to learn complex patterns from raw data [8].

Feature learning methods based on deep neural networks can be applied to recognize facial expressions. Feature matrices are created by extracting landmark points from facial images and these matrices are used to train the DNN model. The constructed model performs the classification of facial expressions [9]. Deep learning methods can be used to build visual tracking applications that capture the objects in a video by a set of actions that are learned with deep neural networks. The deep neural network is trained using different video sequences and tested using actual tracking with variations in target objects in different backgrounds [10].

Drones are smaller vehicles that have gained popularity in recent times due to their low-cost, minimal human intervention and size. They have the advantage of providing real-time information about events through videos and images. Deep learning can be utilized to identify illegal drones that pose greater security risks to the public. Suitable image classification algorithms such as convolutional neural networks can be made use of for this purpose and this converts the sensing data into an image. These methods provide more information and better detection rate of illegal drones [11].

The characteristics of future wireless networks will have greater difficulty levels and this necessitates the improvement of traditional approaches in terms of network design and operations. Simple transmission technology is no longer sufficient to meet the challenges and it will be hard to address the various service requirements of different classifications of users. There is also a need for a dynamic change in network infrastructure concerning the traffic variations and mobility of devices. The reconfiguration and adequate deployment of network resources are vital to ensure

unceasing connectivity in addition to meeting the user demands [12].

Artificial intelligent wireless networks are frameworks that use machine learning and deep learning techniques to impart computers with data and the ability to learn from them. Numerous machine-learning strategies have been used in the design and functioning of communication networks in recent years. Some of them include Decision Trees, Genetic Algorithms, Support Vector Machines, etc.

Deep learning is a technique that has grabbed the attention of the community of users of network communication lately. This technique employs the learning process in data with Artificial Neural Networks (ANN). ANN supports deep learning to be performed effectively on large data in comparison to other strategies. Deep learning in association with ANN has found its applications in several fields including text and speech recognition, language processing, and image classification.

Deep learning algorithms focus on processing very large datasets. The tremendous increase in the volume of data due to the growing number of wireless devices help the implementation of deep learning viable. The progress in computing power enables larger complex algorithms to execute faster. Despite the advantages, two major challenges exist. They are data acquisition and network integration. The majority of contributions in the area of communication networks discuss standard machine learning techniques and they do not emphasize deep learning or applications of ANNs in deep learning.

Machine learning techniques enable generating outputs for formerly unseen inputs. Training an algorithm in a larger dataset helps to minimize error but this is feasible only with increased storage and computation requirements. Machine learning techniques show performance as a function of the data set size. This literature survey reviews the applications of deep learning focusing on the contributions in the area of Wireless Sensor Networks.

One method of generating missing values based on available data values is referred to as the imputation of data. Whenever a time series has a very few discrete missing values, the process of applying statistics brings a good approximation of data. Another method of reconstructing the missing data is to identify the missing parameters from other seen parameters from the dataset. Deep learning methods can also be employed for the recovery of sensor data and these methods show greater performance for larger datasets. The approach of data-driven modeling requires large volumes of training data but the restrictions on wireless sensor networks like limited power supply, poor working conditions enable data to be collected only within limited periods [13].

Deep learning techniques have many levels of hidden layers that help them to learn higher-level information present in the data using non-linear functions [14]. Deep neural networks can be employed to jam data transmissions that can be done by applying the learning process to study the channel traffic and the characteristics responsible for the success of data transmission. Deep learning techniques can be used to make decisions at both the transmitter and jammer levels [15]. Deep learning methods can be used in intrusion detection systems (IDS) for Wireless Sensor Networks. When compared to the traditional machine learning methods, the deep learning-based intrusion detection system is found to provide better detection and rates of accuracy [16].

Improving spectrum utilization in the field of wireless communication systems is a

crucial challenge in wireless communication systems. Cooperative operation by multiple relay nodes is primary to enhance the sharing of transmission paths and to increase throughput. Deep neural networks can be trained and used for choosing optimal relay nodes from a set of relay nodes to effectively model the process of cooperative communications [17].

When wireless multimedia sensor networks are used for monitoring environmental factors, the sensors deployed can be considered as cameras and the network can be treated as a multi-view video system. Wireless transmission of these multi-view videos can result in the loss of video frames. Deep learning techniques can be used to reconstruct the lost frames during transmission and to estimate the missing pixels in the lost frames. This process that uses information from the available neighborhood frames produces an increased average peak signal-to-noise ratio [18].

As a result of the widespread use of the Internet of Things, the use of Wireless Sensor Networks is found to be growing tremendously in recent years. This causes the data acquired to be voluminous. The processing of data is a heavyweight task causing the load on the server to be larger. Several methods like parallel processing, edge computing, and distributed processing have been used for this purpose but these methods do not concentrate on the problems of communication traffic and power usage. Deep learning methods can be applied to address such challenges to reduce the traffic and the load on the sensors based on the processing capacity of the sensor nodes [19].

It is important to build a flood prediction system to control the number of affected victims. Wireless Sensor Networks are capable of retrieving such information and they provide better results in gaining the time series data. Deep learning methods like Multilayer Perceptron (MLP) are good at predicting flood events based on rainfall data and levels of water deposit. They provide better results in predicting the level of water elevation [20].

3. ANALYSIS OF BIOMECHANICAL FEATURES OF PATIENTS: A CASE STUDY

A deep learning technique has been applied to a data set with values those characterize six biomechanical features [21]. These features are used to categorize orthopedic patients in to two classes: Normal and Abnormal. The dataset has multivariate characteristics with the number of instances as 310. There are 6 attributes and the attributes are assigned real values. The attributes include the following: ['pelvic_incidence', 'pelvic_tilt_numeric', 'lumbar_lordosis_angle', 'sacral_slope', 'pelvic_radius', 'degree_spondylolisthesis']. The patient belongs to either of a class ['Normal', 'Abnormal']. The error was calculated using the cross-entropy method and the accuracy metrics are evaluated. The sequential model is adapted and the model is assumed to have two hidden layers. The hidden layers use the ReLU (Rectified Linear Unit Activation Function) activation function and the Sigmoid function is applied to the output layer. Executions performed on the dataset have been recorded with varying number of nodes in the two hidden layers and the accuracy is compared.

Table 1.1 Comparison of accuracy values obtained for different nodes in the hidden layers.

	No. of Nodes in Hidden Layer 1	No. of Nodes in Hidden Layer2	Obtained Accuracy in %
Execution1	4	2	78.06
Execution2	8	4	79.35
Execution3	2	4	67.74

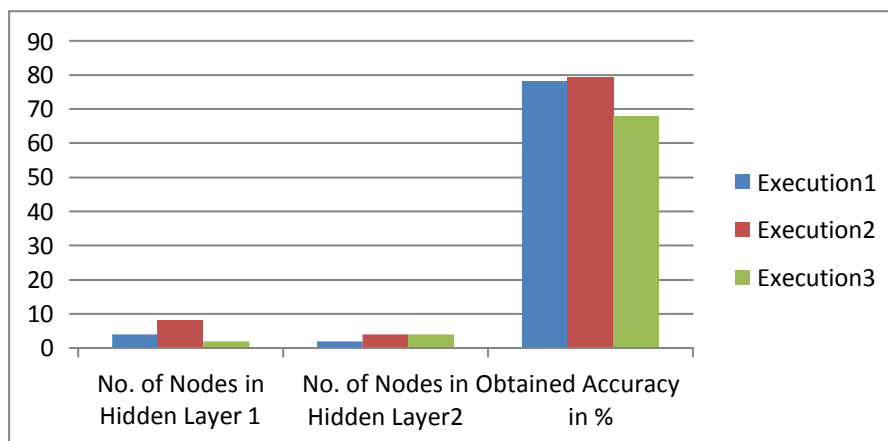
**Figure 1.2: Representation of the accuracy levels with varying number of nodes in the hidden layer**

Table 1.1 shows the accuracy as obtained with a different number of nodes in the two hidden layers. Six attributes that are the input dimensions are the nodes of the input layer and the output layer takes one node for the class (0/1). Execution 1 takes 4 nodes in the first layer and 2 nodes in the second layer and the accuracy of 78.06%. Execution 2 increases the number of nodes in the two hidden layers to 8 and 4 respectively. This resulted in a slightly improved accuracy of 79.35%. The third execution reduced the number of nodes in the first hidden layer to two and the accuracy obtained from this execution is 67.74%. Figure 1.2 shows a pictorial comparison of the different inputs and the achieved accuracies.

4. CONCLUSION

Deep learning has become a crucial tool in handling the complexity of communication networks. The improved data storage technologies in distributed environments and advancements in the field of computer processing make the usage of deep learning techniques very practical in nature. This paper reviews the usage of deep learning in a wide range of applications. The field of deep learning has attracted lots of interest from researchers and it has open research issues that can be addressed with the help of wireless communication networks. The large data to be handled by artificial neural networks without compromising the performance has become a widely focused research problem. Many methods of data analytics require complete data inputs as inadequate data may generate biased results. Yet another research area is the fusion of network architectures with neural network design. Performing deep learning with missing and

corrupted data also gain considerable attention among researchers. Enormous data is required to attain the required performance in deep learning. Wireless communication technologies play a greater role in comparison to other areas of research as it provides large volumes of data. The knowledge obtained from wireless communication enables deep learning to be performed with greater productivity. The paper also presents a case study illustrating the accuracy obtained with varying levels of hidden layers.

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