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# An Overview of Neural Networks and their Applications

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**ABSTRACT:** Neural Networks are inspired from the working of the human brain. Neural Network is a network of several neurons connected to each other in a way that they produce desired output. The way in which these neurons are connected lead to evolution of different types of neural networks. The aim of this paper is to present an overview of the neural networks. The different types of neural networks such as Feed Forward Neural Network, Recurrent Neural Network, Stochastic Neural Network and Modular Neural Network are elaborated in this paper. The most popular neural network today is Convolutional Neural Network (CNN), widely used for object recognition and image classification. This paper also presents a study on CNN that includes study of its unique features and different layers present in it. The Back Propagation (BP) is one of the most common gradient based algorithm used for training a neural network. The different applications of neural networks, mainly image classification, object detection and text recognition are also discussed in this paper.

**KEYWORDS**: Convolution;Layer;Neural Networks;Neuron; Weight

## I. INTRODUCTION

The basic processing unit of an artificial neural network is a neuron. An Artificial Neural Network (ANN) is said to be interconnections between several such neurons. Each neuron in ANN has an activation function $a$ and parameters $\{w, b\}$ associated with it, where $w$ stands for weights and $b$ stands for biases. Theactivation function is a linear combination of the input to the neuron and its parameters, which is followed by element wise non-linearity, which is known as transfer function [4]. A simple activation function can be represented as:

$$a = \sigma(w^T x + b) \quad \text{eq. (1)}$$

where $\sigma(.)$ is the transfer function,
$w^T$ is the transpose of the weight matrix,
$x$ is the input to the neuron,
$b$ is the bias matrix,
Some of the commonly used activation functions are:

- ReLU function:
  Rectified Linear Unit (ReLU) is a piecewise linear function that retains the positive part. It is non-saturated activation function [N7]. This function is represented by:
  $$a_{i,j,k} = \max(z_{i,j,k}, 0) \quad \text{eq. (2)}$$
  where $z_{i,j,k}$ is the input of the activation function at $(i, j)$ location of $k^{\text{th}}$ channel.
  One of the major disadvantage of this function is that it has zero gradient when unit is inactive.
- Leaky ReLU function
  In order to overcome the disadvantage of ReLU function, this function is used given by:
  $$a_{i,j,k} = \max(z_{i,j,k}, 0) + \lambda \min(z_{i,j,k}, 0) \quad \text{eq. (3)}$$
  where $\lambda$ is a predefined parameter in the range $(0,1)$. This function compresses the negative part which gives a small non-zero gradient when the unit is inactive [7].

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The layer which receives the input externally is called as the input layer. The layer of neurons which produces the final output is called as the output layer. All the layers that lie between the input and output layer are called as hidden layers. The simplest ANN will have one input layer, one hidden layer and one output layer [5].
The neural network also consist of a layer called as loss layer. They specify the training of the network affects the deviation between the predicted output value and the actual output value [21]. Some of the commonly used loss functions are Hinge function, Softmax function, Sigmoid function and Euclidean loss.

As the artificial neural networks are data driven, their performance is largely dependent on the quality and the quantity of the data. Apart from the data used for training and testing, the performance of ANN also depends on the computing power and the efficiency of the algorithms used [2].

The rest of the paper is organized as follows: Section 2 contains the literature survey. Section 3 elaborates different types of neural networks. Section 4 illustrates about the convolutional neural networks. Section 5 contains the explanation for the learning algorithms of neural networks. Section 6 summarizes applications of neural networks and Section 7 concludes.

## II. LITERATURE SURVEY

Though the interest of researchers in neural networks has grown in the past few years, the existence of neural networks has been right from 1940s. The very idea of Neurocomputing was first proposed by Warren McCulloch and Walter Pitts [15]. They proposed very simple model that could perform arithmetic or logical operations. They presented ten simple theorems that determined how neurons work and behave when connected in a network.

In 1950s, first neurocomputer was developed by RosenBlatt [16]. In his paper, he presented the working of a model that was mainly focused on pattern recognition. This was known as Perceptron. During the same period, Bernard Widrow developed a slightly varying neural network that was known as ADALINE. Later, in the 1980s, John Hopfield wrote two high quality papers on neural networks that drew attention of researchers and scientists all over the world [17, 18]. In 1982, Hopfield explained the biological interpretation of the neural networks. He stated that the neural networks had asynchronous parallel processing capability which is very useful for providing rapid solutions to computational problems [17]. In 1984, Hopfield studied a large network of neurons that had graded response [18].

The convolutional neural network, the most common one today gained popularity with the huge success of AlexNet in ImageNet Challenge [20]. This network consists of eight layers- five convolutional layers and 3 fully-connected layers. They worked on the ImageNet dataset that consists of over 15 million labeled images which approximately belongs to 22,000 categories. They concluded that even if a single convolutional layer was removed from their system, the error increased drastically.

Since then, many scientists have been working on neural networks and have come up with a variety of them. The most recent advancement in the neural network is the Capsule Neural Network [24]. In this type of network, small group of neurons in the same layer are considered and known as ‘Capsule’. These capsules are represented using a parse tree. Each node in the parse tree corresponds to an active capsule. Through an iterative process, the active capsule in a layer chooses its parent from one layer above it. The output of this capsule is a vector which makes the use of powerful dynamic routing mechanism possible. [24] presents a Shallow Capsule Neural Network, also known as CapsNet, which consists of two convolutional layers and one fully connected layer. This network is found to be very efficient when it comes to dealing with segmentation problems, which are considered the most difficult. timization function will not use that node.

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## III. TYPES OF NEURAL NETWORKS

The categorization of the neural networks is shown below:

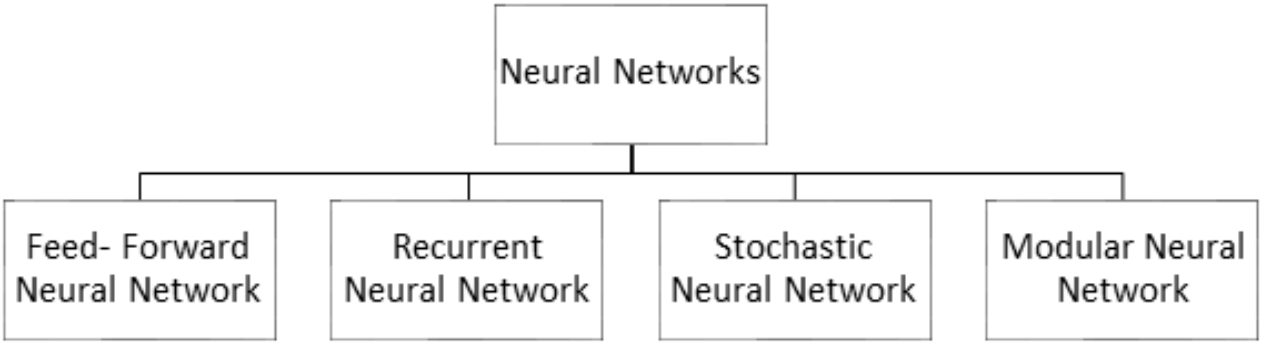


Fig. 1: Classification of Neural Networks

### A. *Feed Forward Neural Network*

The feed forward neural networks are the simplest of all other types. The flow of information is only in one direction. Therefore, there are no cycles and loops in this type of network [6]. The feed forward neural networks are further divided into two types – single layer perceptron and multilayer perceptron.

The single layer perceptron has a single layer of output nodes and the output is obtained from the input through a series of weights. The neurons in this network fire only when the value calculated is above a certain threshold. So, they are known as McCulloch-Pitts or threshold neurons [6]. The single layer perceptron can be used for classifying the linearly separable data only [8].

The multilayer perceptron has several hidden layers between the input and output layer. This allows it to solve complex problems and classify non-linear data with increased generalization [8]. In multilayer perceptron, there are multiple layers of neurons which learn through the algorithm of back propagation, which is explained in the later part of the paper. Convolutional neural network is an example of such a network which is explained in the next section.

### B. *Recurrent Neural Network*

The flow of data in recurrent neural networks is bi-directional. The neurons in recurrent NN are connected to other neurons in the same layer apart from being connected to neurons in the other layers [8]. Simple recurrent networks and Hopfield networks are its types. Simple recurrent neural networks are used for sequence prediction when it is beyond the scope of Multilayer perceptron [6].

Hopfield Neural Network is a type of recurrent neural network which has mutual connections in the network [23]. They can be efficiently used as memory models [8]. The Quarternionic Hopfield Neural Network (QHNN) and Hyberbolic Hopfield Neural Network (HHNN) are major types of Hopfield Neural Network. In Quarternionic Hopfield Neural Network, the network is made up of quarternionic neurons and their conjugates. The Quaternions represent the neuron state and connection weights [23].

### C. *Stochastic Neural Network*

In this type of network, random variations are introduced by the network itself, which make them different from other networks. The neurons are used as stochastic activation functions or the stochastic weights are used in the links [22].

Boltzmann Machines are an example of stochastic neural networks. They can be used for a learning or search problem. These networks compute the probability of the unit value being activated while utilizing the energy of the entire system. These are calculated repeatedly and used for deciding the activating nodes [8]. Training Boltzmann machines can be difficult when there are hidden units. To overcome the difficulties of the Boltzmann Machine,

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another type of it named Restricted Boltzmann Machine is used. It reduces the number of hidden units in the Boltzmann Machines to make it simpler.

D. *Modular Neural Network*

Modular Neural networks have a series of independent neural networks together which are moderated by an intermediary [6]. Each neural network is called a module and these modules do not interact with each other directly. The intermediary takes the input from different modules and processes it to produce output. Committee of Machines (CoM) and Associative Nearest Neighbour (ASNN) are two types of modular neural networks.

## IV. CONVOLUTIONAL NEURAL NETWORKS

The major reason for the popularity of convolutional neural network is the use of convolution operation instead of multiplication. Due to use of convolution, the computations are reduced, thereby reducing the weights [3]. Ultimately, it leads to reduction in complexity of the network, which is a desirable feature. Use of sub-sampling, shared weights and local receptive fields has made them even more popular [2]. Another desirable feature of CNNs is the reduced number of parameters they need to learn [21].

The three main factors during the learning process of a convolutional neural network are sparse interaction, parameter sharing and the equivariant representation [3].

- Sparse interaction makes the size of the kernels smaller, which can be over the entire image, thereby reducing the complexity.
- Only a set of parameters is learnt by the network instead of learning separate sets for each location, which is termed as parameter sharing.
- Due to parameter sharing, the output changes in the same manner as the input which is known as the equivariance property of the network.

A. *Layers in Convolutional Neural Networks (CNN)*

Broadly, there are two layers in a convolutional neural network, namely convolutional layer (c-layer) and sub-sampling (s-layer) [3]. These layers are connected alternately to form a convolutional network. The c-layers are responsible for the feature extraction while the s-layers are responsible for feature mapping.

Specifically, a convolutional neural network typically contains the input layer, convolutional layer, pooling layer, fully connected layer and output layer [2]. Each of these layers have a specific function which is stated below:

- Input layer:
  The input layer is the first layer of convolutional neural network. It takes the raw pixels of the input image or their transformations as input [21].
- Convolutional layer:
  The convolutional layer comes after the input layer. This layer performs the 2D convolution with a variable that controls the depth of the filter, calculated by:

$$L_{ij}^{k} = \tanh\left((w^{k} \otimes x)_{ij} + b_{k}\right) \quad \text{eq. (4)}$$

  where $w^k$ represents the weights,
  $k$ is the $k^{th}$ feature map,
  $\otimes$ is the 2D convolution operator,
  $i, j$ indicate the pixel position,
  $b_k$ represents the bias
  The output of this layer is a feature map.
- Pooling Layer:
  After the convolutional layer comes the pooling layer. It is used for reducing the dimensions of the feature map produced. There are various type of pooling used of which common ones are explained below:
  - Max pooling:
    Max pooling is one of the most commonly used pooling. This is a non-linear form of down sampling. This type of pooling outputs the maximum value by partitioning the feature map into non-overlapping rectangles [20]. Max pooling suffers through the problem of overfitting.

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- Mixed pooling:
  This pooling is a combination of max pooling and average pooling. Due to such a combination, the mixed pooling overcomes the problem of overfitting [7].
- Spectral pooling:
  In this type of pooling, the dimensionality reduction is done by cropping the frequency domain representation of the input [7].
- Stochastic pooling:
  This pooling is used in order to get rid of the overfitting problem. In stochastic pooling, the output value is randomly picked from the activations according to the multi-nominal distribution [7].

- Fully connected layer:
  Fully connected layers are called so because the neurons have full connections to all the activations from the previous layers [21]. These are called as the inner product layers. The class scores are computed by fully connected layers.
- Output layer:
  The output layer is the last layer in the network. It takes the class scores as the input from the fully connected layer and produces the final output.

## V. LEARNING ALGORITHMS FOR NEURAL NETWORKS

Deep learning is becoming popular due to its ability to learn useful features independently [1]. In deep learning techniques, the networks are trained using a gradient based algorithm. In this method, the weights and biases are tuned iteratively in order to get the minimum loss function. For adjustment of these parameters, the derivatives of the loss function are back propagated to each layer. This is known as back propagation algorithm [2]. This is an iterative algorithm and adjusts the weights until the error is less than a specified threshold or remains constant [20]. If there are c classes and N training samples, then the total error is given by:

$$E^N = \frac{1}{2}\sum_{k=1}^{c}(t_k^n - y_k^n)^2 \qquad \text{eq. (5)}$$

where $t^n$ is the corresponding label,
$y^n$ is the predicted value.

The optimal values of the weight and bias are computed using the following formula:

$$w_{t+1} = w_t - \gamma_t \nabla_w \mathbb{E} \qquad \text{eq. (6)}$$

$$b_{t+1} = b_t - \gamma_t \nabla_b \mathbb{E} \text{eq. (7)}$$

where $\gamma_t$ is the positive learning rate.
Though this method is widely used, it has several disadvantages like local minima, model selection uncertainty and slow convergence.

[2] presents an approach of training neural networks known as Neural Networks with Random Weights. In this approach, the hidden weights and biases are selected at random from a defined range and kept constant. The weights between the hidden layer and the output layer are obtained analytically. This algorithm is very easy to implement has possesses the capability of universal approximation.

## VI. APPLICATIONS OF NEURAL NETWORK

In this section, some of the major applications of different types of neural networks are listed.

### A. *Image Classification*

Image classification is one of the most common application of neural network right from the beginning. The neural networks find a lot of applications in the field of agriculture. [11] presents one such example where the convolutional neural networks are used in order to detect the weeds present in the farm. This helps the farmers in site specific weed management. This paper showed that sufficient number of training samples for each species of weed can lead to high classification accuracy.

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Neural networks play an important role in medical field as well. [10] shows how Artificial Neural Networks are used for detecting Cervical Cancer, which is difficult to detect as it occurs without any symptoms. The use of ANN for this purpose has proved to be accurate when compared to manual methods like LCB test or Pap smear.

Recently, CNNs have been used along with some other strategies in order to make them more efficient. [9] presents a modified version of traditional CNNs to classify the hyperspectral images. They proposed a model that combined the multi-resolution analysis theory and CNNs in order to extract three-dimensional (3D) features from the images. This model is known as 3D MWCNNs which are found to be very accurate than any state-of-the-art methods.

B. *Object Detection*

Neural networks, especially the convolutional neural networks is becoming the state-of-the-art method for object detection and image classification. One of the most challenging and recent research in this field is the pedestrian detection. This proves to be helpful in surveillance systems. [12] presents a pedestrian detection system based on convolutional neural networks. From the experiments, it was evident that the system was successful in detecting the pedestrians in real time.

The neural networks are also being used for social causes and one such is detecting the pornographic content in the images. [13] shows the use of deep convolutional neural networks for detection of pornographic content in the given images. The system proposed is less complex and gives accurate results.

C. *Text Recognition*

Text recognition is mainly used for handwriting recognition. It is a challenging task due to different writing styles. [14] have used the neural networks for improving the Chinese language recognition systems. They conducted experiments using only Feed Forward Neural Network Language Model (FNNLM) and only Recurrent Neural Network Language Model (RNNLM). It was found that only neural networks did not give a significant change. So, they combined FNNLM and RNNLM, known as Hybrid Language Model (HLM), which gave the best results.

[20] presents a Chinese Menu Recognition App that enables the users to capture name from the Chinese menu and get the English name and the image for the same dish. It uses the Deep CNN that consists of three convolutional layers, two max pooling layers and a fully connected layer. The paper concluded that this app performed better than Google Translate App when the noisy or low resolution images of Chinese text were given as input.

## VII. CONCLUSION

Neural Networks have been around since two decades now, but have gained popularity recently due to advancement in processing and storage capacity of the computers. A brief summary of neural networks is presented in this paper. Different ways of connections between the neurons, the basic unit of neural network, lead to different types of neural network. These types of neural networks are explained along with their subtypes. The feed forward neural networks have unidirectional flow of information. The recurrent neural networks have dynamic nature, which increases their efficiency as well as complexity. While feed forward NN and recurrent NN consist of one single network with multiple connections between neurons, the modular NN consists of several independent neural networks, each being called a module. As the complexity of the problem increases, the complexity of the neural network being used increases.

The most popular neural network, Convolutional Neural Network is a type of Multilayer Feed Forward Neural Network. The CNNs learn through the Backpropagation learning algorithm, a gradient based algorithm. To overcome the disadvantages of BP algorithm, the random weights approach can be used.

Neural networks have a wide range of applications. Some real world applications of neural networks include vehicle recognition for intelligent traffic management, medical image classification to automate the medical processes, object detection which can be used for object tracking and image classification.

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