

Analysis of various classification techniques based on neural networks

¹Maninderpreet Singh Puri, ²Amrit Kaur

¹M. Tech Scholar, ²Assistant Professor

¹Department of Computer Engineering,
Punjabi University Patiala,
Patiala, India

Abstract: Artificial Intelligence is one of the fastest growing fields in the scientific community and many companies like Google are implementing Artificial Intelligence techniques for getting their user's preferences for various business/marketing oriented clients. Manufacturing industries are now using automated machines for producing products and these robots are more reliable and less reluctant to make errors. Scientists are developing new technologies which run on simulated human brains that can act like humans, understand the language and perform tasks. Artificial intelligence is present everywhere, from the mobile phones we carry that are tracking our locations to monitor our daily activities to modern watches which can track our daily sleep, heart rate, calories burnt and based on information can suggest how to improve lifestyle. In the field of military, robots which can inspect the enemy areas are very beneficial for making strategic plans and in a catastrophic situation, rescue operation can be carried out by robots that can go to places where humans cannot go. The aim of this paper is to highlight some of the current techniques that are used in Artificial Intelligence (Artificial Neural Networks). Also, it elucidates the advantages, disadvantages, methods/functions, inputs/data sets, results used in experiments for different applications. Techniques described in the paper are Neural Networks, ANN, Convolution Neural Networks, Deep Neural Networks, Feed Forward Networks and other prominent methods used in applications for classification of data.

Index Terms -Artificial Intelligence, Neural Networks, Classification, Deep Neural Networks, Feed Forward Neural Networks, Convolution Neural Networks.

I. INTRODUCTION

A. WHAT IS ARTIFICIAL INTELLIGENCE?

The concept of using knowledge by which machines can perform human-like sophisticated tasks, resulting in highly intelligent machines having human-like intellect is Artificial Intelligence. As humans are considered most intelligent species on earth as compared to other living creatures, these characteristics of reasoning, abstract thinking, and performing complex actions based on current knowledge can be used by systems and such machines can be called artificial intelligence machines.

Reference [3] In the 1980s and 1990s, some researchers attempted to use the neural network algorithm to solve various machine learning problems by simulating the human brain cognitive mechanism. Reference [1] The Newell and Simon (1976) suggested the physical symbol system hypothesis which introduced the concept of a set of entities called symbols which pointed that every intelligent machine has a group of entities (knowledge base), which can be combined to form an expression (new set of knowledge). These expressions can be modified, reproduced, destroyed (actions) for certain uses. These symbolic models are not only used in areas such as game playing, but also in areas such as visual perception where this process is more operational.

B. WHY ARTIFICIAL INTELLIGENCE?

The current world needs faster ways to solve mundane tasks and expert tasks which can reduce consumption of lot many resources. Also, these machines can also help solve various problems which have always been very difficult to decode, like predicting the future of some scenario based on current assumptions. It can work to discover, predict, and solve unknown, uncertain, complex forms of problem paths so that progress can be made quickly.

C. ARTIFICIAL INTELLIGENCE TECHNIQUES PREREQUISITES

Artificial Intelligence Techniques are used to solve a broad category of problems under a single umbrella. The techniques can be applied to a range of problems. For this knowledge should have some properties-

1. The knowledge should be represented in such a way that generalizations can be made: rather than separating each individual situation, it should be clubbed together on the basis of common properties. If it is not oriented, then more memory and operations would be required. Without this property, we call it "data" rather than "knowledge".
2. It should be provided in the terms that people can understand.
3. It should be modify-able to make improvements.
4. It can be utilized even if it is in not of the workable form.

D. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks is one of the two major streams of Artificial Intelligence another being Expert systems. Reference [6] ANNs have the ability to model linear and non-linear systems without the need to make assumptions implicitly as in most traditional statistical approaches. The technology of neural networks in machine learning is based on inspiration from known facts on how the brain works. It basically uses the natural working of brain cells to store and transfer information using neurons present in the brain. Neurons are small storing, processing units in the brain, which are connected with another neuron cells in the brain in a network. Every neuron receives the electrical

signals from its dendrites through a bunch of different neurons, which goes to the central part of the cell for processing. Each cell has a set threshold value and when the signal strength exceeds the limit the cell sends an output signal to the next neuron through an axiom.

Reference [1] The Perceptron, an invention of Rosenblatt [1962], was one of the earliest neural network models. Fig. 1 A Perceptron models a neuron by taking a weighted sum of its inputs and sending the output of 1 if the sum is greater than some adjustable threshold value (otherwise it sends 0).

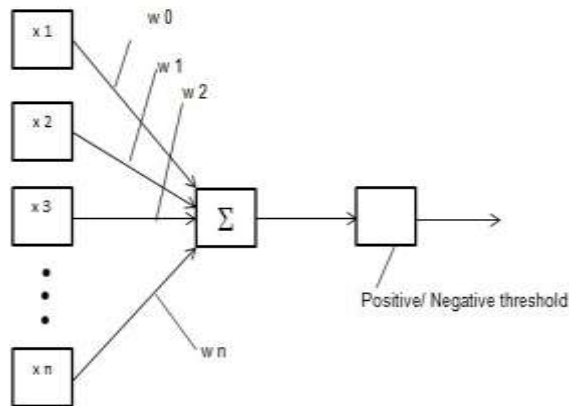


Fig 1. A perceptron/neuron

The inputs (x_1, x_2, \dots, x_n) and connection weights (w_1, w_2, \dots, w_n) in the figure are typically real values, both positive and negative. If the presence of any characteristics of “ x_i ” tends to cause the Perceptron to fire, then the weight “ w_i ” will be positive; if the feature “ x_i ” inhibits then the weight “ w_i ” will be negative. The process of learning is adjusting the weights and threshold values. The Perceptron will fire when the weighted sum is greater than zero. Fig. 2 A Perceptron computes the inputs as a binary function and many Perceptrons can be combined to compute more sophisticated functions. The output of this neuron can be expressed by Equation:

$$z = f\left(\sum_{i=1}^N w_i x_i + b\right)$$

Where $f(z)$ is the activation function and b is the default bias. Fig. 3 Such a group of Perceptrons can learn to compute the correct function by analyzing various inputs and outputs. ANN is further divided into two categories feed forward neural networks and back propagation networks. Reference [1] The units or Perceptrons are organized in a way that defines the network architecture Networks with interconnections that do not form any loops are called feed forward neural networks (FFNN) and the one which forms loops with previous layers is called back propagation networks (BPN). The tasks to which artificial neural networks are applied tend to fall within the broad categories of functional approximation, classification, and data processing. Imitating the functioning of the human brain, ANN is a tool of great importance in prediction as well.

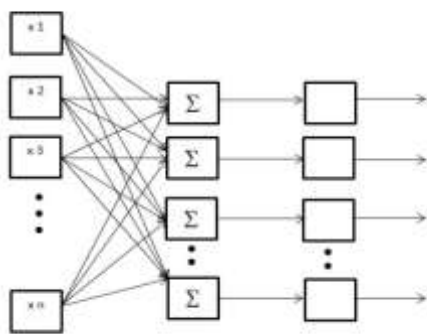


Fig 2. A group of perceptrons/neurons

Recurrent or non-feed forward networks are utilized where one or more loops of interconnections are used for a particular application.

II. LITERATURE REVIEW

A. DEEP NEURAL NETWORKS

These days neural networks are used to classify various inputs of data, such as audio, video, text which is done by neural network training in order to improve the clustering of information. Different techniques are used such as Support vector machines (SVM), Random Forest (RF), Boosting and K-Nearest neighbor classifier but these all are shallow techniques. Deep neural networks (DNN) use more layers and deeper networks, which works better than shallow methods SVM and boosting [3] As Zhaojin Zhang explained the advantage of deep neural networks. Fig. 4 Three-layer neural network model, including an input layer, a hidden layer, and an output layer, can be approximated by any classification function.

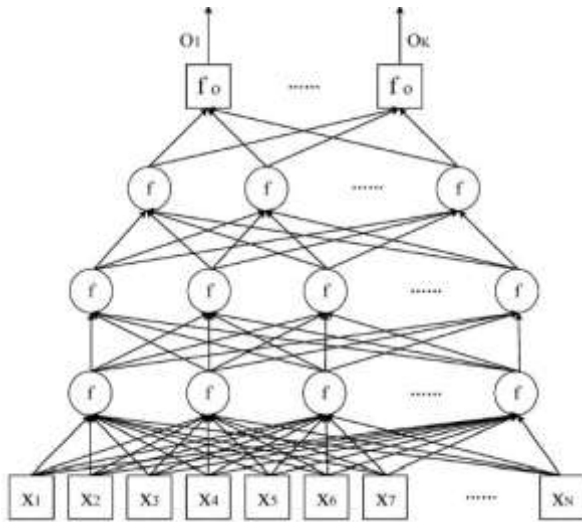


Fig 3. Deep neural networks (DNN)

Given all that, why we need deep learning?

Reference [7] Deep learning has brought a revolution in the field of machine learning, showing improved performance over traditional approaches. In biomedical imaging, Deep Neural Network (DNN) based systems won both the International Symposium on Biomedical Imaging 2012 Challenge on segmentation of neuronal structures in electron microscopy stacks [8], and the International Conference on Pattern Recognition contest 2012 on analysis of large medical images for cancer detection [9]. Besides use in classification, one of the most powerful aspects of deep learning is that they eliminate the need of designing features, as they can learn them from the raw data. Moreover, DNNs have been shown to outperform tailored feature extraction in medical image analysis [10] and the state-of-the-art in lung cancer classification in computer tomography images [11].

Recently, researchers have shown that if the depth of the model is not enough, computing units to be required will increase exponentially for a given task. It means that the shallow models expressing the same classification function need much more parameters and training samples.

In the experiment conducted by Zhaojin Zhang on the image set comprising of roads and vehicles, he took 150 random images from the internet with different noise and pattern. Images were taken from the back of vehicles.



Fig 4. Sample of images used

Reference [3] The test results show that the effects of the model are better and can gain the clearer classification recognition results. With the increasing number of iterations, the mean error and misclassification rate will decrease and tend to be stable. Conventional single layered neural networks showed a relatively less accuracy as compared to DNN. This shows that deep neural networking is a better technique for classifications.

Another experiment conducted by Kuo-Yi, Lin, Jeffrey, J.P., Tsai used a deep-learning based tool for forecasting areas which require improvement in functionality and store development to enhance customer experiences. This tool is utilized by administrative level of the pharmacy and uses POS (Point-of-Sales) from the cash register and weather reports as data sets. The data obtained from their system helped them to improve their executive policies which included allocation of resources to enhance the quality of service in all aspects. Reference [6] The study proposed a data-driven framework consisting of six phases for extracting user product aesthetic experience: (1) understand and define the problem, (2) identify the niche for decision quality improvement, (3) structure of Business Activity Analysis, generate the alternatives, and clarify the influence relationships among uncertain events, (4) sense and describe expected outcomes, (5) overall interpretation, and (6) Decision Optimization, the detail illustration is provided in the Fig. 5.

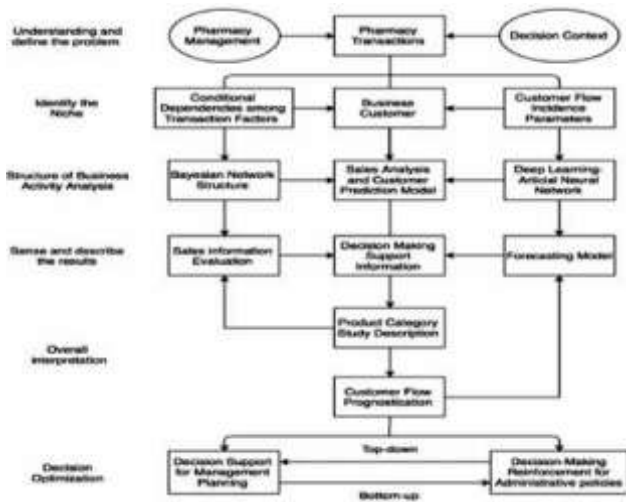


Fig 5. Framework driven by data for refining decision making process

In the business activity and analysis part of the framework they used two artificial intelligence techniques, Bayesian network structure for getting insights about data possible for reaction among factors for sales analysis and deep learning ANN to develop a prediction model of customer by using data sets as a reference point.

B. CONVOLUTION NEURAL NETWORKS

Another research paper by [4] Hulya Yalcin showed classification of plants by using Convolutional Neural networks (CNN). The paper described how automatic identification of plants based on spatiotemporal patterns extracted from their visual appearances can help in the application of pesticides, fertilization, and harvesting of different species on-time in order to improve the production processes of food and drug industries.



Fig 6. Growth stages of corn

The traditional method of plant identification is very expensive and time-consuming. It requires manual labor, which observes the fields in order to get the information about the crops. The agricultural sector is one of the main economic resources of many nations. The conventional manual techniques rely upon the ability of the observer, but using artificial neural networks it can be improvised. An agriculture monitoring system has already been implemented by using sensors which store huge amounts of images in their database in Turkey through TARBIL project in 2012. Reference [4] Exploring recent artificial intelligence methods like CNN to automatically classify plants are vital for the improvement of the recognition accuracy. CNN models are an extension of deep learning of artificial networks. They consist of multi-hidden Layer Perceptrons (MLPs) which involve multiple convolution, pooling, rectified linear unit (ReLU), and fully-connected layers.

In another experiment by Srinivas S S Kruthiventi, Kumar Ayush, and R. Venkatesh Babu, they proposed a fully convolutional neural network called DeepFix which is used to predict human eye fixations or mechanism of visual attention with the help of saliency prediction. This model learns in a hierarchical manner and predicts the map from one end to another end. According to [12] human visual system is dictated by two kinds of attention mechanisms: bottom-up and top-down [13]. Bottom up factors, which are derived entirely from the visual scene, are responsible for the automatic deployment of attention towards discriminative regions in the scene. The involuntary detection of a red colored STOP sign on the road, while driving, is an example of this attention mechanism. This kind of attention is automatic, reflexive and stimulus-driven. On the contrary, the top-down attention mechanism is driven by internal factors such as subject's prior knowledge, expectations and the task at hand, making it situational and highly subjective [14]. It uses information available in the working memory, thereby biasing attention towards areas of the scene important to the current behavioral goals [15]. The selective attention exhibited by a hungry animal while searching for its camouflaged prey is an example of the top-down mechanism.

In this experiment, the DeepFix was inspired by Visual Geometry Group (VGG) network which is a very deep network comprised of 20 convolutional layers, having small kernel size and is applied on images in a sequence. They introduced a new method LBC (Location Biased Convolutional filters), which helps the DNN to learn location dependent patterns.

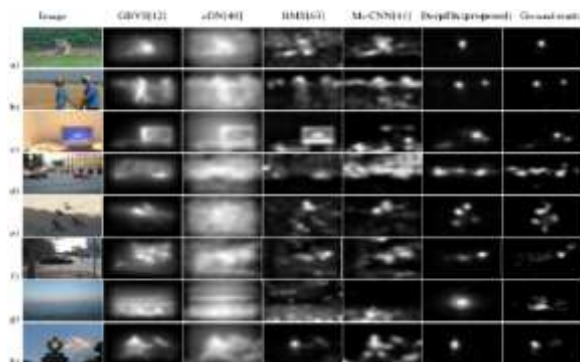


Fig 7. Reference. [13] Qualitative results of the proposed method on validation images

They compared the results with other methods (GBVS, eDN, BMS, Mr-CNN) and found that DeepFix is able to perform better as compared to other methods with a considerable margin.

C. Feed Forward Neural Networks

Fig. 5 Another experiment by Charlyn Pushpa Latha to classify human emotions using Electromyogram Signals showed that how facial expressions can be used to extract certain patterns of emotions by using Facial Electromyography (FEMG) signals. Reference [5] The experiment used six discrete emotions, namely anger, disgust, fear, happy, neutral and sad. In this study, audiovisual stimuli were used for evoking emotions. Fig. 6 The FEMG signals are recorded using AD Instrument and Bio Amplifier attaching 5 gold plated electrodes to the subject. In the signal recognition phase, a static Feed Forward Neural Network (FFNN) and a dynamic Elman Neural Network (ENN) were used to identify the six emotional states from the FEMG signals.

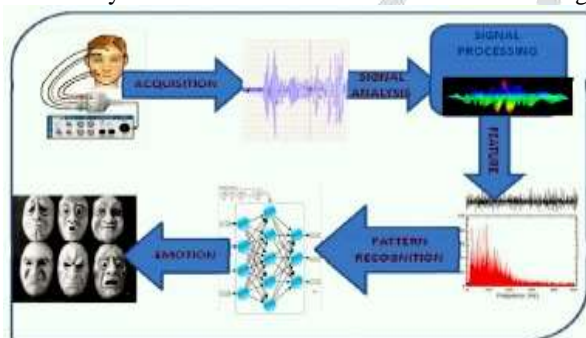


Fig 8. Facial emotional recognition system overview

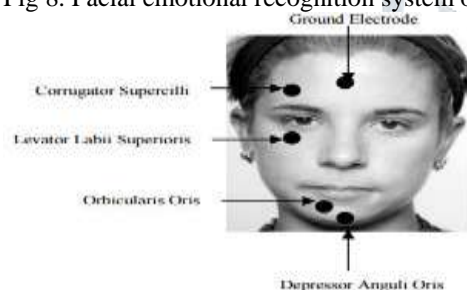


Fig 9. FEMG electrode placement

FFNN is a biologically inspired classification algorithm. Reference [5] It consists of a large number of simple neuron-like processing units, organized in layers. Every unit in a layer is connected with all the units in the previous layer. Each connection may have a different strength or weight. The weights on these connections encode the knowledge of a network. Data enters at the input and passes through the network, layer by layer until it arrives at the output. During normal operation, that is when it acts as a classifier, there is no feedback between layers. This is why they are called Feed Forward neural networks. Reference [5] ENN is a type of the dynamic recurrent neural network, which consists of two-layer back propagation networks with an additional feedback connection from the output of the hidden layer to its input. ENN with one or more hidden layers can learn any dynamic input-output relationship arbitrarily well, given enough neurons in the hidden layers. In the test results, it was found that the performance of ENN is comparatively better than FFNN. The identification is better in the case of females as compared to males.

III. ANALYSIS

All the experiments showed that some techniques are better than others in particular cases with respect to their inputs and expected outputs.

According to Zhaojin Zhang, Cunlu Xul, and Wei Feng the problem which occurs with feature extraction and classification of images from the rear view of vehicles using neural networks is the training of the neural networks with many parameters and over-fitting problems. Also, training using dataset requires more computer resources and long computing time for even small networks, as compared to other models. Reference [3] Faced with such a large number of practical problems, neural networks have gradually been replaced by some better methods emerging in the 21st century, such as Support Vector Machines (SVM), Random Forest (RF), Boosting and K-Nearest Neighbor Classifier (KNN). These techniques can replicate the properties of neural networks containing one or two hidden layers. However, they further explained that these techniques are shallow techniques and deep neural networks have deeper structure and more layers which can reduce the parameters

and training samples. Moreover, in the experiment, they compared the results in terms of accuracy rate achieved by neural networks (NN) and deep neural networks (DNN).

In research conducted by Kuo-Yi, Lin, Jeffry, J.P., Tsai, they used a data driven framework to support decisions for administrative levels and other function in a customer/ retail based pharmacy. Although, the whole process was divided into many subparts, but the most important aspect of the framework was to build a deep-learning based customer forecasting tool which is further divided into- problem definition, data processing, model definition and development, and finally evaluation.

In the first step, datasets were collected from pharmacy cash register and weather datasets were collected from Taiwan Central Weather Bureau platform. In total, 36538 of raw information was collected from POS which included attributes date, time, transaction number, category, membership ID, product serial, quality of items, transaction total cost and others. The dataset was integrated into 89 days and was further utilized in the prediction model. The weather dataset was segregated into 7 attributes namely: temperature, humidity, perception, raining hours, wind speed, and sunshine hours which represented the weather conditions in the region where the pharmacy was located.

In the preprocessing phase, data is filtered for redundancies, inconsistent values, missing values in case of POS and reducing the complexity by taking average temperature and humidity as main variables for the experiment in weather data set, respectively. Timings were restricted to 8:00 am- 11:00 pm. They used MATLAB tools to normalize the data and to find a relationship between variables date, weekday, Mean value and Relative Humidity.

In the next step [6] Neural Network is applied to forecast the daily number of customers by input time information and weather condition, including date, weekday, mean temperature and relative humidity. Backpropagation network is used to build the forecasting tool. Training functions used in the experiment were Trainlm (Levenberg-Marquardt), Trainbfg (BFGS Quasi-Newton), and Trainscg (Scale conjugate Gradient) which are built-in functions in MATLAB. However, Levenberg-Marquardt performed better as compared to other two functions. Moreover, one hidden layer is applied to Neural Network model with 5-15 neurons and one layer for output. Using the model they developed Graphical User Interface which is used by the pharmacy as a decision-making tool. The output showed an overall accuracy of 84.2%. To confirm the accuracy of the model, comparisons were made between the information forecasted by the model and the actual information from the pharmacy. The model is applicable in different retail businesses such as clothing, footwear, supermarkets, and hotels.

In research conducted by Hulya Yalcin, Salar Razavi on plant classification, they implemented convolution neural networks which used a combination of multi-hidden layers perceptrons (MLPs) adding multiple convolutions, pooling, Rectified linear unit (ReLU), and fully functional layers. However, challenges were faced during preprocessing steps due to illumination changes and de-blurring of images caused by seasonal changes. The results were compared with support vector machine (SVM) classifier embedded with different kernels as well as descriptors such as Local binary patterns (LBP) and GIST. Yalcin & Razavi used pre-trained convolution neural networks to classify plant species in 16 classes. The dataset contained multiple images of the same plant taken during the growth stages of plants.

In research by Srinivas S S Kruthiventi, Kumar Ayush, and R. Venkatesh Babu, they used DeepFix which is designed to capture logical information at multiple scales while keeping the global factors into account with the help of larger receptive fields. Generally, convolutional neural networks cannot model location dependent patterns, for example, center-bias. Hence, Srinivas S S Kruthiventi, Kumar Ayush, and R. Venkatesh Babu came up with a new technique called Location Biased Convolutional Layer. In this experiment, they proposed an approach for modeling bottom-up visual attention mechanism by predicting human eye fixation. According to their study, most of the saliency models are based on multi-scale low-level visual attributes such as text and color. For a mixture of low-level (color, text, orientation) and high-level (faces, text) feature detection deep neural network is considered suitable. Their model is inspired by VGG network with 20 convolutional layers [13] each of a small kernel size, operating in succession on an image. The network is designed to capture object-level semantics, which can occur at multiple scales, efficiently through inception style [16] convolution blocks. Each inception module consists of a set of convolution layers with different kernel sizes operating in parallel. The global context of the scene, which is crucial for saliency prediction, is captured using convolutional layers with very large receptive fields. These layers are placed towards the end of the network and replace the densely connected inner product layers commonly present in convolutional nets. Reference [16] To summarize, the key features of the proposed DeepFix Network are:

- Large depth - to enable the extraction of complex semantic features.
- Kernels of different sizes operating in parallel - to characterize the object semantics simultaneously at multiple scales.
- Kernels with large receptive fields - for capturing the global context.
- Location biased convolutional layers - for learning location dependent patterns such as the center-bias present in eye fixations.

Moreover, they evaluate the proposed network on multiple challenging saliency datasets MIT300 [17], CAT2000 [18], PASCALS [19], OSIE [20], FIGRIM [21], SALICON Test Set [22], iSUN Test Set and showed that it achieved state-of-the-art results on these datasets.

In the experiment by Charlyn Pushpa Latha G, Hema C.R, Paulraj M.P on the classification of human emotions using Facial Electromyography, they used static Feed Forward Neural Network (FFNN) and dynamic Elman Neural Network (ENN). Experimental results show that the performance of ENN is comparatively better than FFNN. The table shows the comparisons of all the techniques used in experiments along with their inputs, methods, results and future scope.

Table 1 Comparison of techniques

Experiment by	Technique (s)	Input (s) or dataset (s)	Method (s)	Result (s)	Future Scope (s)
“Road Vehicle Detection”- Zhaojin Zhang, Cunlu Xul' and Wei Feng2 [2]	Deep Neural Network (DNN) v/s Neural Networks (NN)	<ul style="list-style-type: none"> • 150 Images with rear views of vehicles with background noise. • Images are preprocessed and zoomed to 32*32 with 	The s-shaped function is selected for activation functions in hidden layers; back propagation algorithm is adapted in the training process.	<ul style="list-style-type: none"> • DNN is superior. • The advantage is not obvious when the number of samples is less in deep neural networks. • The rates of error of the vehicle classification of 	Selecting superior feature extraction methods (PCA (Principle component analysis), Wavelet

		different brightness, contrast ratios, and conditions.		DNN and NN are 3.34% and 6.67%.	transform, Gabor transform) before vehicle detection, classification phase can increase the accuracy of vehicle detection and classification.
“Plant Classification”-Hulya Yalcin, Salar Razavi [4]	Convolution Neural Networks (CNN) v/s Support Vector Machine (SVM)	<ul style="list-style-type: none"> The Dataset of images (2-D plant images) is used having followed the dimensions: width of map* height of map*color channels of the map. 4800 images organized into 16 different classes. 	<p>CNN</p> <ul style="list-style-type: none"> Many hidden layer perceptrons are used with many convolutions, pooling, ReLU function and fully connected layers at each step. For specific output, the input maps are convolved with distinct kernels and convolution layers share its weights in the same output map. The convolutions are combined with pooling layers to reduce dimensions and increase speed. <p>SVM</p> <ul style="list-style-type: none"> The SVM based classifier uses features such as LBP and GIST with RBF and polynomial kernels schemes. 	<ul style="list-style-type: none"> Experimental results indicate that an approach based on CNN is significantly effective with an accuracy of about 97.47% for classifying 16 kinds of plants compared to other methods. Results suggest that the classification accuracy of CNN based approach outperforms other methods. 	Future work can consist of building different architectures, with a variety of activation functions, as well as experimenting pre-processing methods to enhance classification performance by improving the machine learning layer.
“DeepFix: A fully Convolutional Neural Network for predicting human eye fixation”-Srinivas S S Kruthiventi, Kumar Ayush, and R. Venkatesh Babu. [13]	Convolutional Neural Network, Visual Geometry Group (VGG) network, & Location Bias Convolution	<ul style="list-style-type: none"> The network takes an image of size $W * H * 3$ (RGB image) as input. Evaluate the proposed network on multiple challenging saliency datasets MIT300 [17], CAT2000 [18], PASCALS [19], OSIE [20], FIGRIM [21], SALICON Test Set [22], and iSUN. 	<ul style="list-style-type: none"> A series of 5 convolutional layers each having a max pool layer at the end. All convolutional layers in the network are followed by Rectified Linear Unit (ReLU) activation to introduce element-wise nonlinearity. While training the weights in 5 layers, VGG-16 net has been used. Layer 6 & 7 are inception block & Location Biased Convolutional layer which are designed to have very large receptive fields by introducing bigger holes in kernels as compared to initial layers. 	<ul style="list-style-type: none"> The results obtained show that the proposed method achieves state-of-the-art results on all the datasets. 	LBC is a novel technique which can be used in other images processing systems that require processing of center biased images and need to analyze different aspects of images.
“Classification	Feed Forward	<ul style="list-style-type: none"> Facial 	<ul style="list-style-type: none"> Raw FEMG signals are 	<ul style="list-style-type: none"> Maximum 	Improving the

of Human Emotions”- Charlyn Pushpa Latha G, Hema C.R, Paulraj M.P [5]	Neural Network (FFNN) v/s Elman Neural Network (ENN)	Electromyography (FEMG) signals are used for six different emotions. <ul style="list-style-type: none"> 12 Features are extracted from each emotion. A dataset of 420 samples is collected from seven subjects. 	processed using notch and Chebyshev filters. <ul style="list-style-type: none"> FFNN and ENN are designed using 12 input neurons, 3 output neurons, and 5 hidden neurons. 75% of the dataset is used for training and 100% for testing the network. 	recognition rates of 94.32% and 94.78% were achieved for FFNN and ENN respectively. <ul style="list-style-type: none"> From the experiment, it is observed that the performance of ENN is comparatively better than FFNN. 	recognition accuracy of the facial emotion recognition system using better features and classifiers.
“A Deep learning-based customer forecast tool”- Kuo-Yi, Lin, Jeffrey, J.P., Tsai [6]	Bayesian Network & Artificial Neural Network	<ul style="list-style-type: none"> 36538 of raw information collected from point of Sales (POS) with many attributes that was integrated into 89 days. Weather dataset with 7 attributes collected from Taiwan Central Weather Bureau platform. 	<ul style="list-style-type: none"> Bayesian network for getting insights about data possible for reaction among factors for sales analysis. Neural Network with one hidden layer having 5-15 neurons and one layer of output is used to forecast the daily number of customers. Backpropagation network is used to build the forecasting tool. Training functions used in the experiment were Trainlm, Trainbfg, and Trainscg which are built-in functions in MATLAB. 	<ul style="list-style-type: none"> The output showed an overall accuracy of 84.2%. Trainlm (Levenberg-Marquardt) performed better as compared to other two functions. 	The model is applicable to different retail businesses such as clothing, footwear, supermarkets, and hotels.

IV. APPLICATIONS

The possible applications of the techniques mentioned above are vast in size. Some the applications in manufacturing industries include monitoring of various faults during the production of spare parts, food product quality inspections, identifying defective pieces in appliances. Neural networks are also currently in use by many auto-manufacturing companies like Tesla, which runs reinforcement learning (RL) a machine learning method closely related to classification for running vehicles in autopilot mode, these can also be used in drones to reach their destination by selecting shortest paths between point A to B using GPS and road vehicle driving technology. In the medical field, these techniques can be used to classify various types of diseases based on the symptom and behavior classifications. The very same technology can be used to cluster a specific set of images to derive meaningful structures inside a big collection of data. Marketing on websites uses the customer browsing patterns to learn about the habits of the clients and utilizes them to prioritize their preferences.

V. CONCLUSION

Neural Networks are nowadays used in business applications, and in certain fields, such as financial management, production, operations, and business forecasting. This study is a comprehensive study of selective techniques used in recent times, which use neural networks and introduces some potential ideas for implementation of neural networks to solve a vast number of problems. Further research could be extended on using ANN predictions for more fields such as military robots, identification of characters of human genes and using DNN for self-learning technologies to make robots.

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