

Comparative Study and Utilization of Best Deep Learning Algorithms for the Image Processing

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ABSTRACT- Deep learning has gained immense popularity in scientific computing, and its algorithms are widely used in complex problem-solving industries. Every deep learning algorithm use different types of neural networks to perform indented tasks. Deep learning (DL) algorithms have emerged from different machine learning and soft computing methodologies. Since then, a number of deep learning (DL) algorithms have been recently introduced in the scientific community and applied in various application fields. Today, the use of DLs has become indispensable due to their intelligence, effective learning, accuracy and reliability in model creation. However, a comprehensive list of DL algorithms has not yet been presented in the scientific literature. This article lists the most popular DL algorithms and their application areas. Deep learning uses ANN artificial neural networks to perform convoluted calculations on huge amounts of data. It is a type of machine learning based on the structure and function of the human brain. Deep learning algorithms train machines by learning from examples. Industries such as healthcare, e-commerce, entertainment and advertising often use deep learning.

KEYWORDS- Deep learning, machine learning, convolutional neural networks (CNN) recurrent neural networks (RNN), autoencoder (DAE), deep belief networks (DBNs), long short-term memory (LSTM), review, survey, state of the art.

I. INTRODUCTION

Deep Learning makes use of synthetic neural networks to carry out complicated computations on big quantities of data. It is a kind of system mastering that works primarily based totally at the shape and feature of the human mind. Deep Learning algorithms teach machines through mastering from examples.

Industries inclusive of healthcare, e-commerce, entertainment, and marketing and marketing regularly use deep mastering. A neural community looks as if the human mind and is made of synthetic neurons, additionally referred to as nodes. These nodes are stacked subsequent to every different in 3 layers:

- Input layer
- Hidden layer
- Output layer

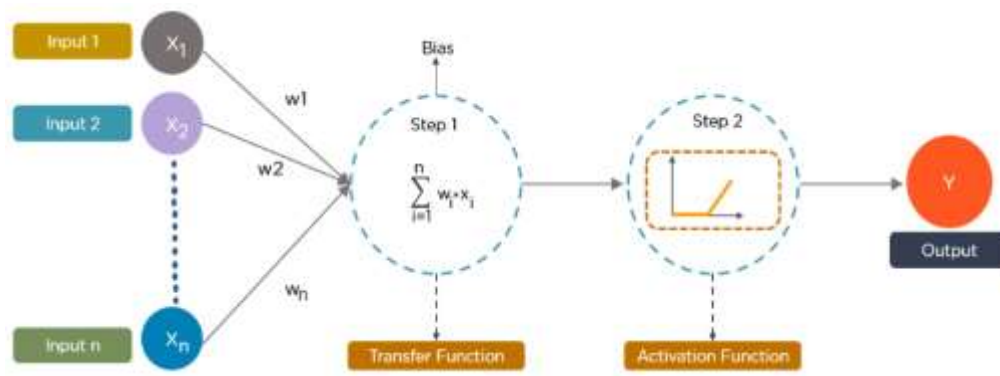


Figure 1: Data provides information to each node

In Figure 1 above, Data provides information to each node in the form of inputs. This node computes by multiplying the input with random weights and adds a bias. Finally, we apply a non-linear function, also called an activation function, to determine which neurons fire. Deep learning algorithms have a self-learning representation, but rely on ANNs that reflect how the brain computes information. During the training process, the algorithm uses unknown elements of the input distribution to extract features, group objects, and discover useful data patterns. As with a self-learning training machine, this is done at multiple levels with the algorithms used to create the model. Deep learning models use multiple algorithms. No network is considered perfect, but some algorithms are better suited to perform

certain tasks. A solid understanding of all the major algorithms is critical to choosing the right one.

II. LITERATURE REVIEW

It is a commonly used neural network based on supervised learning in which information flows in one direction and has no loops. The main goal is to find an optimized function $f(\theta)$ that maps the input to the desired output and learn its optimized bias value (θ) . When there is a discrepancy between the expected and actual outputs, the MLP learns using a backpropagation algorithm by adjusting the connection weights. Their main applications are solving optimization problems in finance[2], transportation, fitness, and energy in figure1.

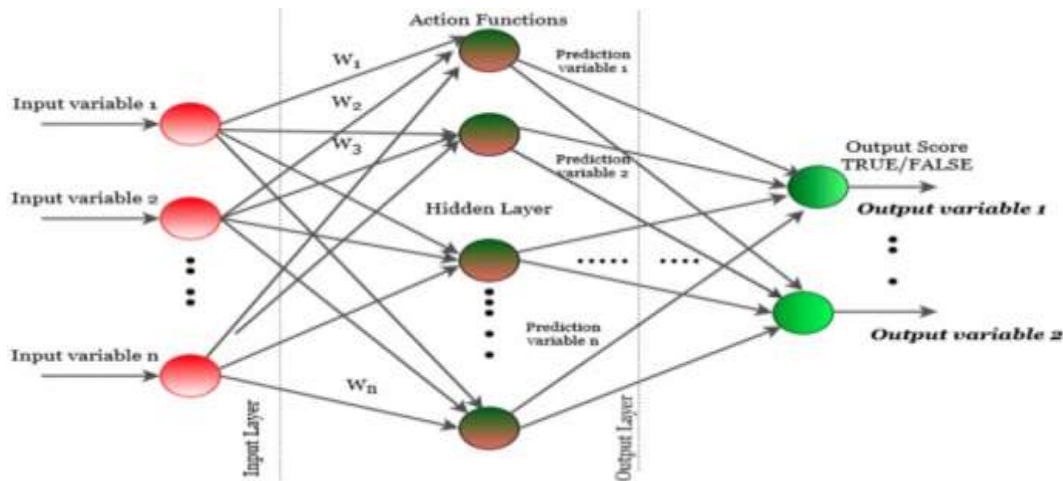


Figure 2: Solving optimization problems

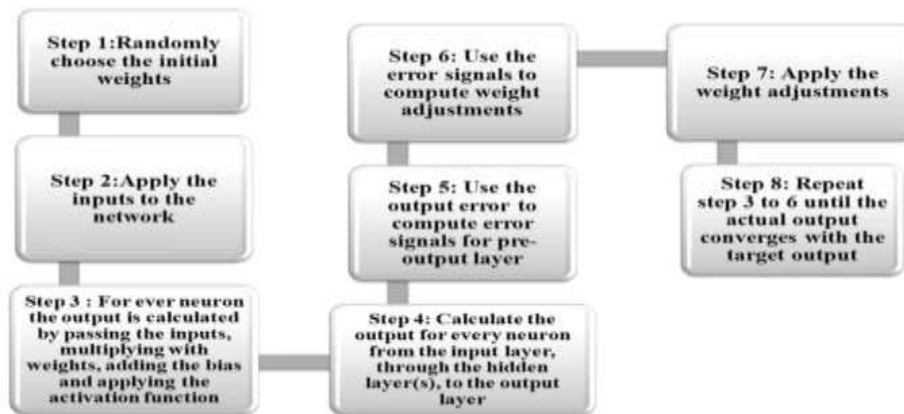


Figure 3: MLP algorithm step

The figure 3 shows the Steps in MLP algorithm. Deep learning has garnered prominence over the last several decades for groundbreaking applications in areas such as image classification, speech recognition, and machine translation [3]. A Multilayer Perceptrons (MLP) is an artificial neural network with three or more layers of perceptrons. These layers are a single input layer, one or more hidden layers, and a single output layer of the perceptrons[5].

A. Limitations of MLP, SOM, and DBN

Algorithms MLP with backpropagation has a weak ability to generalize to statistically neutral problems. Therefore, the model does not know the expected output, it is determined by the relationship between different input variables. MLP is fully connected and has too many parameters, leading to redundancy and inefficiency [6]. MLP ignores spatial information when solving problems.

SOM minimizes the volume of the dataset, making it easier to visualize and form clusters.[7]

However, it has some drawbacks, such as poor handling of categorical variables. Solutions for huge amounts of data[9] are computationally intensive and can be inaccurate. According to DBN[8], it takes a lot of energy and space to run. Huge demand for random number generators (RNGs) makes deep belief networks less energy efficient. This paper also compares the performance of the proposed method to benchmark standards such as pixel-based MLP, spectral texture-based MLP, and context-based CNN classifiers. Md Manjurul Ahsan et al. [5] proposed a hybrid model that uses a combination of convolutional neural networks (CNN) and multi-layer perceptrons (MLP). Here MLP processes numerical/categorical data and CNN extracts features from his X-ray images.

For parameter matching, we used a grid search method to determine the number of hidden layers, number of neurons, epochs, and stack size. Meha Desai and others [6] compared and analyzed the functionality and design of MLPs and CNNs for the application of breast cancer detection in their study, concluding that CNNs provide slightly higher accuracy than MLPs.

B. Properties of MLPs

- Property 1: Universal MLP can learn both linear and nonlinear functions. MLPs are designed to approximate

arbitrary continuous functions and solve problems that are not linearly separable.

- Property 2: Adaptive learning and optimality MLPs can learn how to perform tasks from information about their training and initial experience. MLP minimizes the loss function. Therefore optimal By learning the ability to map inputs to outputs, loss can be reduced to acceptable levels.
- Property 3: Probabilistic MLP is a probabilistic program. Stochastic programs use probability distributions to solve very complex optimization problems in which some or all of the problem parameters are uncertain.
- Property 4: power of the abyss Compared to flat meshes, deep meshes can represent some features more compactly. A parity function and a deep mesh whose size is proportional to the number of inputs computed.
- The following Table Shows the Different types of algorithms used in the deep learning approach.

C. Convolutional Neural Networks (CNNs)

CNN, also known as ConvNet, consists of several layers and is mainly used for image processing and object recognition. Yann LeCun developed his first CNN in 1988 under the name of his LeNet. It was used to recognize characters such as postal codes and numbers. CNNs are widely used for identifying satellite images, processing medical images, forecasting time series, and detecting anomalies. CNN has multiple layers to process and extract features from data.

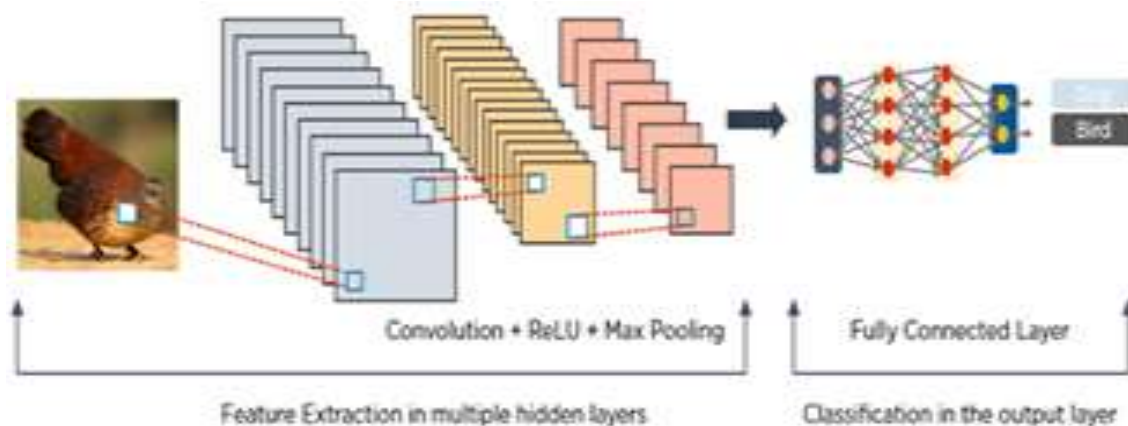


Figure 4: An example of an image processed via CNN

In the above figure 4, the CNN contains a convolution layer with multiple filters to perform convolution operations. A Rectified Linear Unit (ReLU) CNN has a ReLU layer to perform operations on the elements. The output is a modified feature map.

- The cleaned feature maps are then fed to a pooling layer. Pooling is a down sampling process that reduces the dimensionality of feature maps.
- A pooling layer smoothes the 2D arrays resulting from the pooled feature maps into a single long continuous linear vector. A fully connected layer is formed when the

flattened matrix from the pooling layer is fed as input to classify and identify images.

D. Long Short Term Memory Networks (LSTMs)

LSTM is a type of recurrent neural network (RNN) that can learn and remember long-term dependencies. Retrieving long-term historical information is the default behavior. LSTM stores information over time. Useful for time series forecasting as it remembers previous inputs. An LSTM has a chain-like structure with four interacting layers communicating in unique ways. In addition to time series prediction, LSTMs are commonly used for speech recognition, composition, and drug development. it works

like this First, they forget irrelevant parts of the previous state

- Then selectively update the cell's state value
- Finally, the output of specific parts of the cell state

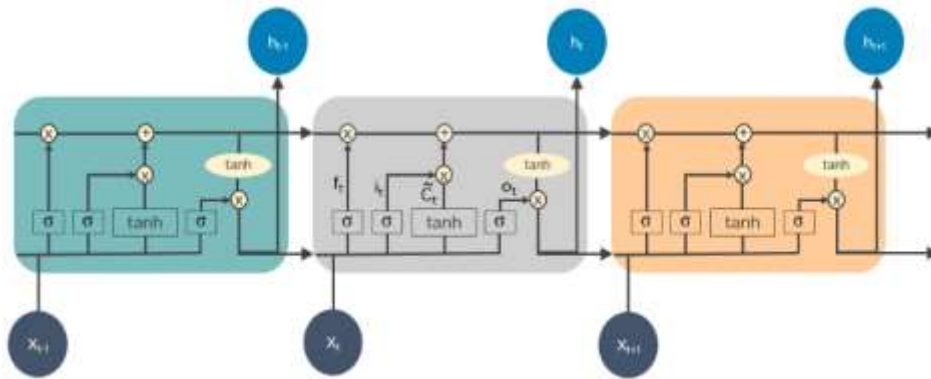


Figure 5: An unfolded RNN looks like this

E. Recurrent Neural Networks (RNNs)

An RNN has connections that form a directed cycle, allowing the output of an LSTM to feed as input to the current phase. The output of the LSTM becomes the input for the current phase, and internal memory allows you to save previous inputs. RNNs are most commonly used for image captioning, time series analysis, natural language

processing, handwriting recognition, and machine translation. it works like this

- The output at time t-1 is fed to the input at time t.
- Similarly, the output at time t is fed to the input at time t+1.
- RNNs can handle inputs of arbitrary length.
- Calculations take historical information into account and model size does not increase with input size.

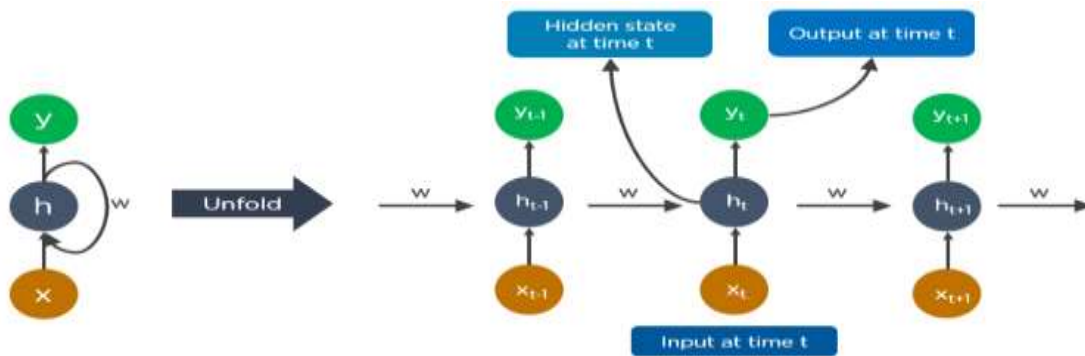


Figure 6: Here is an example of how Google's auto completing feature works

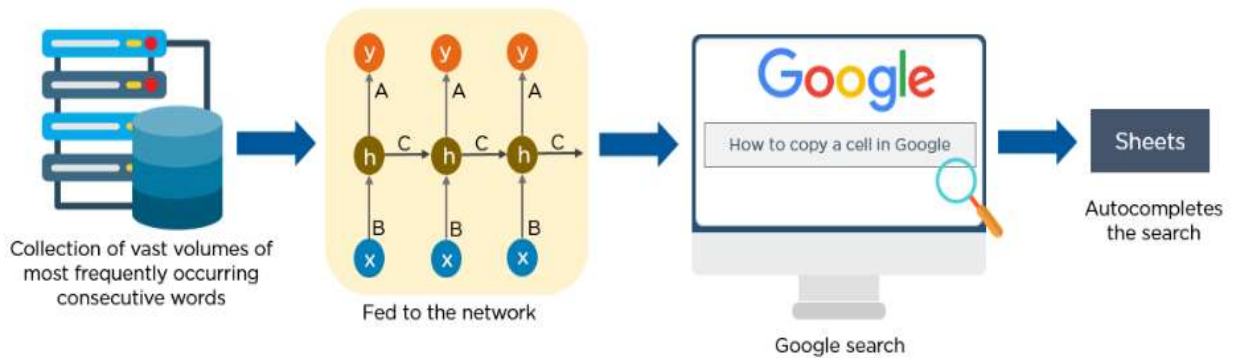


Figure 7: How Google's auto completing feature works

F. Generative Adversarial Networks (GANs)

A GAN is a generative deep learning algorithm that creates new data instances that resemble the training data. A GAN consists of her two components: a generator that learns to generate fake data and a discriminator that learns from this fake information. The use of GANs has increased over time. They can be used to enhance astronomical images and simulate gravitational lensing effects for dark matter exploration. A video game developer uses GANs to upscale his 2D low-resolution textures of old video games by recreating the images in his 4K and higher resolutions through his training. GANs are useful for creating realistic images and cartoon characters, creating photographs of human faces, and rendering 3D objects.

- The discriminator learns to distinguish between fake generator data and real sample data.
- During initial training, the generator produces fake data and the discriminator quickly learns to recognize that it is wrong.
- GAN sends results to generators and discriminators to update the model.

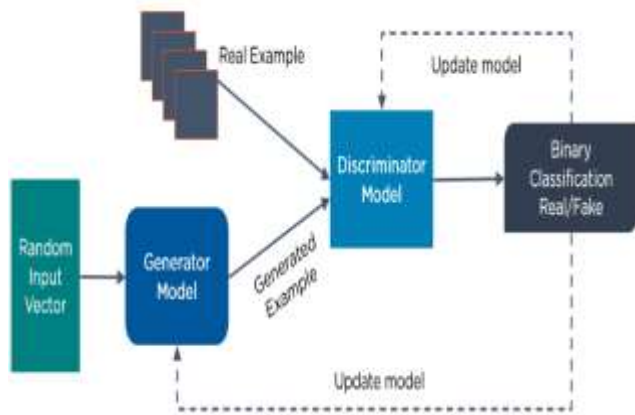


Figure 8: Diagram of how Gans Operate

G. Radial Basis Function Networks (RBFNs)

RBFNs are special types of feedforward neural networks that use radial basis functions as activation functions. They have an input layer, a hidden layer, and an output layer and are mostly used for classification, regression, and time-series prediction.

- RBFNs perform classification by measuring the input's similarity to examples from the training set.

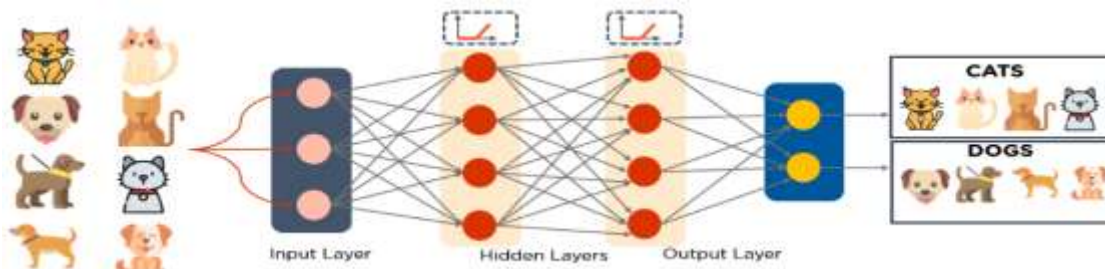


Figure 10: Computes weights and bias and applies suitable activation functions to classify images of cats and dogs

- RBFNs have an input vector that feeds to the input layer. They have a layer of RBF neurons.
- The function finds the weighted sum of the inputs, and the output layer has one node per category or class of data.
- The neurons in the hidden layer contain the Gaussian transfer functions, which have outputs that are inversely proportional to the distance from the neuron's center.
- The network's output is a linear combination of the input's radial-basis functions and the neuron's parameters.

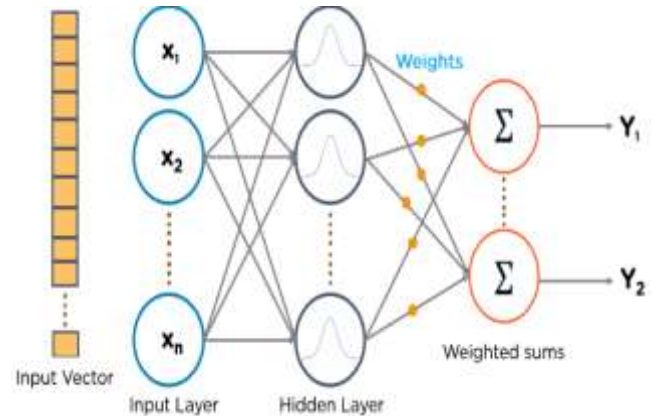


Figure 9: Flow diagram of RBFN

H. Multilayer Perceptrons (MLPs)

MLP is a great place to start learning about deep learning technologies. MLPs belong to the class of feedforward neural networks with multiple perceptron layers with activation functions. An MLP consists of fully connected input and output layers. It has the same number of input and output layers, but can have multiple hidden layers and is used to build speech recognition, image recognition, and machine translation software.

- MLP feeds data to the input layer of the network. Layers of neurons are connected in a graph so that the signal travels in one direction.
- MLP computes the input using the weights that exist between the input and hidden layers.
- MLPs use activation functions to determine which nodes to activate. Activation functions include ReLU, sigmoid functions, and tanh.
- MLP trains models to understand correlations and learn dependencies between independent and target variables from a training dataset.

I. Self-Organizing Maps (SOMs)

Professor Teuvo Kohonen invented SOM, which allows visualization of data that reduces the dimensionality of the data through self-organizing artificial neural networks. Data visualization attempts to solve the problem that humans cannot easily visualize high-dimensional data. SOMs are created to help users make sense of this high-dimensional information.

- SOM initializes weights for each node and randomly selects vectors from the training data.
- SOM goes through each node to find out which weight is the most likely input vector. The winner node is known as the Best Matching Unit (BMU).
- SOM detects his BMU neighbors and the number of neighbors decreases over time.
- SOM assigns gain weights to sample vectors. The closer a node is to his BMU, the greater the weight change.
- The farther away a neighbor is from her BMU, the less she learns. SOM repeats step 2 N times.

The below diagram of an input vector of different colors. This data feeds to a SOM, which then converts the data into 2D RGB values. Finally, it separates and categorizes the different colors

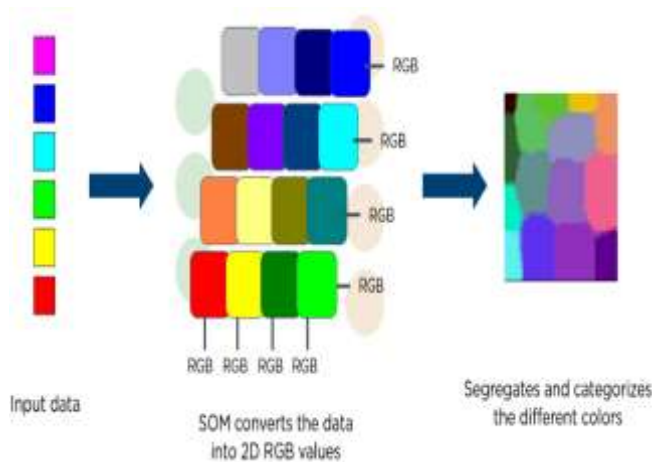


Figure 11: Input vector of different colors

J. Deep Belief Networks (DBNs)

DBNs are generative models composed of multiple layers of stochastic, latent variables. The latent variables have binary values and are often referred to as hidden units. DBNs are a stack of Boltzmann machines with interconnections between layers, and each RBM layer communicates with both the previous and subsequent layers. Deep belief networks (DBNs) are used for image recognition, video recognition, and motion capture data. Greedy learning algorithms train DBNs. The greedy learning algorithm uses a layer-by-layer approach to learn the top-down generative weights. DBNs perform the Gibbs sampling steps on the top two hidden layers. In this phase, the RBMs are sampled as determined by the top two hidden layers. DBNs sample the visible entities using a single pass of the ancestral sample through the rest of the model. DBNs learn that the latent variable values present in each layer can be derived by a single bottom-up pass.

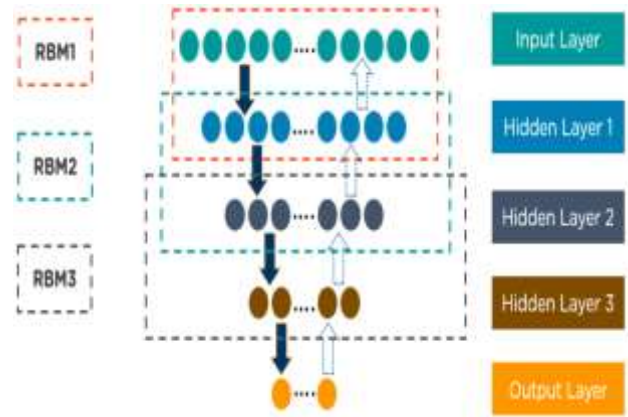


Figure 12: Below is an example of DBN architecture

K. Restricted Boltzmann Machines (RBMs)

Developed by Geoffrey Hinton, RBMs are stochastic neural networks that can learn from a probability distribution over a range of inputs. This deep learning algorithm is used for dimensionality reduction, classification, regression, collaborative filtering, feature learning, and topic modeling. RBMs form the building blocks of DBNs. RBMs consist of two layers: Visible units Hidden units Each visible unit is connected to all hidden units. RBMs have a bias unit connected to all visible units and the hidden units, and they have no exit nodes. RBMs have two phases: forward pass and reverse pass. RBMs accept the inputs and translate them into a set of numbers that encode the inputs into the forward pass. RBMs combine each input with individual weights and an overall bias. The algorithm forwards the output to the hidden layer. On reverse traversal, RBMs take this set of numbers and translate them to form the reconstructed inputs. RBMs combine each activation with individual weighting and overall distortion and forward the output to the visible layer for reconstruction. At the visible layer, the RBM compares the reconstruction with the original input to analyze the quality of the result.

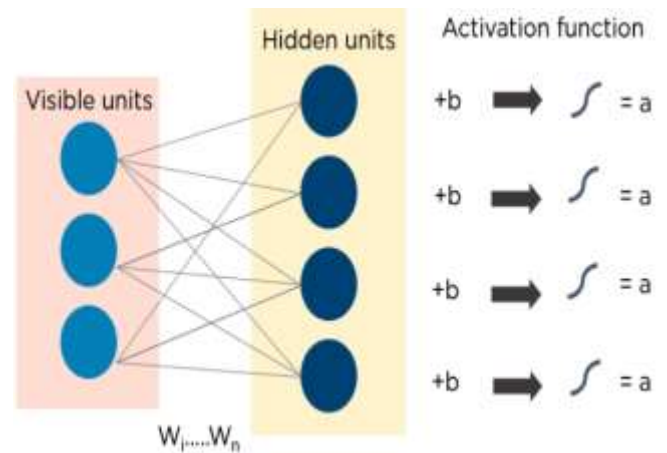


Figure 13: RBM

L. Autoencoders

Autoencoders are a specific type of feedforward neural network where the input and output are the same. Geoffrey Hinton designed autoencoders to solve unsupervised learning problems in the 1980s. They are trained neural networks that replicate the data from the input layer to the output layer. Autoencoders are used for purposes such as pharmaceutical discovery, popularity prediction, and image processing. An autoencoder consists of three main components: the encoder, the code and the decoder. Autoencoders are structured to take an input and convert it into a different representation. They then attempt to reconstruct the original input as accurately as possible. If an image of a digit is not clearly visible, it is fed into an autoencoder neural network. Autoencoders first encode the image and then reduce the size of the input to a smaller representation. Finally, the autoencoder decodes the image to produce the reconstructed image.

The following image demonstrates how autoencoders operate

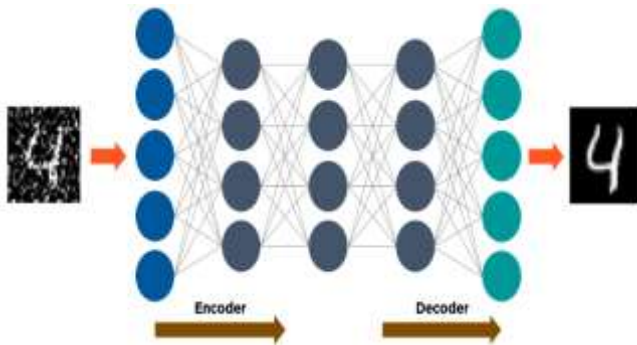


Figure 14: AUTO CODES flow chart

III. OBJECTIVES

Deep learning has garnered prominence over the last several decades for groundbreaking applications in areas such as image classification, speech recognition, and machine translation. A Multilayer Perceptrons (MLP) is an artificial neural network with three or more layers of perceptrons. These layers are a single input layer, one or more hidden layers, and a single output layer of the perceptrons.

The data flows in a single direction, that is forward, from the input layers-> hidden layer(s) -> output layer as in fig.2

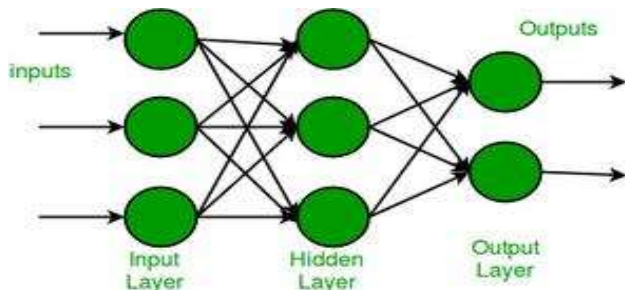


Figure 13: Data flows

Backpropagation is a technique where a multi-layer perceptron receives feedback on the resulting error and the MLP adjusts the weights accordingly to make more accurate predictions in the future. MLP is used in many machine learning techniques such as classification and regression. These have been shown to provide highly accurate results, especially for classification problems. Regression is a supervised machine learning technique that approximates continuous-valued variables. It is commonly used to forecast/predict values based on the values of independent variables. A regression problem can be thought of as having a single output neuron with no activation function. Multilayer Perceptrons (MLPs) were previously used in computer vision, now followed by Convolutional Neural Networks (CNNs). MLP is currently considered inadequate for modern advanced computer vision tasks. It has the property of a fully connected layer where every perceptron is connected to every other perceptron. The downside is that the total number of parameters can be quite large (number of perceptrons in layer 1 multiplied by # p in layer 2, multiplied by # p in layer 3...).

This is inefficient in such high dimensions due to the redundancy. Another drawback is that spatial information is not taken into account. Takes a flattened vector as input. A lightweight MLP (2-3 layers) can easily achieve high accuracy using the MNIST data set. There was a time when MLPs were modern neural networks. MLPs continue to look simpler and simpler as neural network architectures become more complex, deeper, or evolve. The following Table1 shows the various algorithms in today’s market.

For higher overall performance and image category the use of far off sensing, there are various convolution neural network-primarily based totally models. The control of land resources, city planning, catastrophe tracking, and site visitors tracking are all made feasible thank you in massive component to the feature that VHR far off sensing photograph scene category performs in far off sensing research. A VHR (Very High Resolution) photograph scene category version with 3 levels turned into proposed with the aid of using Osama A. Shawky et al. [3]. These levels blanketed statistics augmentation to study sturdy functions, a pre-educated CNN version to extract functions from the unique photograph, and an adaptive gradient set of rules multi-layer perceptron to growth the classifier’s accuracy.

With the advent of modern remote sensing techniques, various hyperfine spatial resolution (VFSR) datasets are commercially available. These VFSR images opened up many possibilities, including: B. Describing urban land-use relief, agriculture, and canopy. Zhang et al. [4] proposed a hybrid classification system that combines the context-based classifier CNN and pixel-based classifier MLP with a rule-based decision fusion strategy. Decision fusion rules are formed based on the context-based confidence distribution of his CNN classifier. Confidence is high if the input image blob is in a uniform region. On the other hand, if the image pixels contain other land cover classes as relevant information, confidence is low. As a result, MLP can fix the classified pixels at the pixel level with low confidence.

IV. CONCLUSION

Deep learning has evolved over the past five years, and deep learning algorithms have become widely popular in many industries. If you are looking to get into the exciting career of data science and want to learn how to work with deep learning algorithms. The work analyzed a total of three predictive accuracies A Completely Different Convolutional Neural Network Let's take a look at the most popular works and records. The main aim was to discover the accuracy of Create different networks on a constant dataset and evaluate them Consistency of predictions from each of these Multilayer Perceptrons. That is It should be noted that difficult frames generally occur. Check and acknowledge network disruption scene. Using Deep Learning and Multilayer Perceptrons Networks plans to rise only in the long term.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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