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A Review on Tomato Leaf Disease Detection using Deep Learning Approaches

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Abstract— Agriculture is one of the major sectors that influence the India economy due to the huge population and ever-growing food demand. Identification of diseases that affect the low yield in food crops plays a major role to improve the yield of a crop. India holds the world's second-largest share of tomato production. Unfortunately, tomato plants are vulnerable to various diseases due to factors such as climate change, heavy rainfall, soil conditions, pesticides, and animals. A significant number of studies have examined the potential of deep learning techniques to combat the leaf disease in tomatoes in the last decade. However, despite the range of applications, several gaps within tomato leaf disease detection are yet to be addressed to support the tomato leaf disease diagnosis. Thus, there is a need to create an information base of existing approaches and identify the challenges and opportunities to help advance the development of tools that address the needs of tomato farmers. The review is focussed on providing a detailed assessment and considerations for developing deep learning-based Convolutional Neural Networks (CNNs) architectures like Dense Net, ResNet, VGG Net, Google Net, Alex Net, and LeNet that are applied to detect the disease in tomato leaves to identify 10 classes of diseases affecting tomato plant leaves, with distinct trained disease datasets. The performance of architecture studies using the data from plantvillage dataset, which includes healthy and diseased classes, with the assistance of several different architectural designs. This paper helps to address the existing research gaps by guiding further development and application of tools to support tomato leaves disease diagnosis and provide disease management support to farmers in improving the crop.

Keywords- Agriculture, Tomato leaf disease, review, deep learning, Convolutional Neural Network (CNN), Dense Net, ResNet, VGG Net.

I. INTRODUCTION

Agriculture has been the primary source of income for the world as well as for India's majority of people. In India, agriculture provides 58% of the livelihood for Indians. Agriculture has become more than a food source for the world and India also Agriculture is the backbone of our country. Village authorities assist farmers in choosing the best crop for their needs. Crop production, on the other hand, is fraught with difficulties. They may also be made simple with the help of technology [1-12].

Tomatoes are a common crop in agriculture; India ranks second in the world for tomato production, and they are also helpful in everyday human kitchens. Tomato consumption has risen dramatically in recent years, but tomato agriculture has been hampered by a variety of diseases and soil conditions, as well as climate change and other environmental factors. The country has a lot of territories where tomatoes can be grown. Tomatoes are grown in Madhya Pradesh, Andhra Pradesh, Karnataka, Tamil Nadu, Orissa, etc and they are susceptible to diseases such as bacterial spots, fungus, algae, etc. Tomato leaf diseases are caused by organic causes. Non-living elements that induce plant diseases include temperature imbalances, chemical toxicity, incorrect fertilizer, rainfall, nutritional inadequacy, and so on. Tomatoes are high in vitamin C, potassium, vitamin K, and folate [13-23], among other vitamins and minerals. Tomato leaf diseases include Bacterial Spot, Early Blight, Late _Blight, Leaf_mould, Septoria Leaf Spot, Spider Mites, Target_Spot, Tomato_Yellow_Leaf Curl Virus, and Tomato Mosaic Virus. Due to a lack of sufficient understanding, it might be difficult for farmers to identify the diseases effectively [13-23].

Deep learning can be used to identify tomato plant diseases. Deep learning can accomplish object recognition and disease classification more precisely than machine learning because it uses multiple neural network convolution methods. Deep learning algorithms include LSTM, GAN, CNN, RNN, and others. Deep Learning will be used to detect and classify tomato leaf diseases using images. The Convolutional Neural Network is one of the most used deep neural networks. CNN offers a self-learning system for extracting characteristics from images and categorizing them [24-65]. It has lately achieved incredible results in a wide range of applications, including the detection

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and classification of plant diseases. Traditional learning algorithms perform admirably when used on datasets and with features that have been carefully built by hand, but they are unable to generalize their results to test cases that come from a variety of distributions. Deep learning is distinguished from other, more common methods by its use of automatic feature learning; nonetheless, for the model to generalize to test examples from a different distribution, it requires a large training sample with a diversified feature distribution [24-75].

II. CLASSIFICATION OF TOMATO LEAF DISEASES

Planting tomatoes most diseases, which include bacterial spots, fungus, algae, and other organisms, are caused by bacterial spots, fungus, algae, and other organisms. The healthy class of tomato plant leaf and the 9-leaf disease class of tomato plant leaf diseases are the two classifications. 18160 images from the PlantVillage Dataset were used to test validation. Tomato plant leaves are infected with a variety of diseases. In tomatoes, there are nine Classes of diseases and healthy classes as shown in Fig1: 1) Target-Spot 2) Mosaic-Virus, 3) Bacterial-Spot, 4) Late-Blight, 5) Leaf-Mold, 6) Yellow-Leaf-Curl Virus, 7) Spider-Mites: Two-spotted spider mite, 8) Early- light, and 9) Septoria Leaf-Spot and Healthy class diseases Tomato plant leaf disease, sometimes known as late blight, was extremely harmful [24-75].

Fungal Diseases: About 85 percent of plant diseases may be traced back to fungi or organisms with similar structures. To infect other plants and trees, fungi, and bacteria only need to land on a nearby surface, as they are so tiny and light. Besides being susceptible to insect pests, tomatoes are also susceptible to several fungal diseases that create replay disease spots on the plant's leaves, stems, and fruit. Diseases caused by fungi in tomatoes are often exacerbated by wet, humid conditions.

At first look, the symptoms of the three most frequent fungal infections of tomatoes appear to be relatively similar, but a closer investigation should reveal which fungus is to blame. Three Types of Fungal Infections are Early-blight, Late-blight, and Septoria-Leaf spot, Leaf-Mold [24-75].

Bacterial Diseases: Bacteria of over 200 different varieties cause it. Insects, splashing water, other infected plants, or equipment can all transmit the illness. It is caused by Xanthomonas bacteria, namely Xanthomona's performance, and only affects green tomatoes, not red ones. As with peppers, diseases have spread to peppers. The disease tends to spread more during the rainy seasons. Spots on the leaves and fruits reduce crop output and can even kill plants or cause them to wither and die from sun damage. Symptoms include spots on the leaves that range from angular to irregular and wet to dry and buy or scabby spots on the fruit. The leaf dots may have a golden halo around them. Cores lose moisture and become brittle over time [24 - 75].

Viral Diseases: It is the rarest sort of plant disease and is caused by viruses. However, there are no chemical therapies for a virus after it has been infected, thus all suspicious plants should be destroyed to halt the infection. They must physically penetrate the plant, and insects are the most common carriers [24 - 75].

By examining various diseases, we can see the various sorts of surgeries and aspects that must be considered. Several disease variations are discussed in further detail.

Bacterial Spot: Spots generated by the bacterium Xanthomonas are called bacterial infections. When combined with high temperatures, heat, and rain, it can cause crops to lose their leaves and get damaged [24 - 75].

Early blight: Fungi or bacteria are responsible for early blight. On elder leaves, little black dots develop first. Infected leaves might become brown and fall off, or they can become dead, dry leaves that attach to the stem [24 - 75].

Late Blight: Fungal pathogen viruses are responsible for late blight. Symptoms of late blight in leaves include water-soaked lesions with an uneven outline and a lighter halo ring [24 - 65].

Leaf Mold: Known scientifically as a fungus, Leaf Mold thrives in damp conditions [24] and high relative humidities (above 85%). Yellow dots on the upper leaf surface are a replay indicator of the diseases [24 - 75].

Septoria Leaf spot: Septoria Leaf Spot is a fungal infection that affects the leaves. It usually appears on the lower leaves after the first fruit has formed. Per leaf, there are many circular regions with dark brown borders and multiple dots. The leaves turn yellow, then brown [24], and eventually, wither if there are multiple leaf lesions [24 - 75].

Two-spotted spider mite: The two-spotted spider mite causes white spots to form on tomato leaves. Diseased areas appear on plant leaves, and the leaves turn yellow or grey before falling off after many days of heavy pest feeding [24 - 75].

Target spot: The ideal growing conditions for tomatoes are temperatures between 68 and 82 degrees Fahrenheit and leaf wetness intervals of up to 16 hours. On leaves, it causes necrotic tumors to form in circular patterns [24 - 75].

Target Mosaic virus: The yellowing and shrinking of tomato plants caused by the tomato mosaic virus is a major cause of crop failure caused by this virus. Curled, distorted, or abnormally small leaves are symptoms [24 - 75].

Yellow leaf curl Virus: To put it simply, the Yellow Leaf Curl Virus causes massive economic losses in tropical and subtropical regions. The fungus gnats, a type of bug, is the vector for this disease. Leaf size is drastically reduced, and the leaves curl or cup upward, as a result of this disease [24 - 75].

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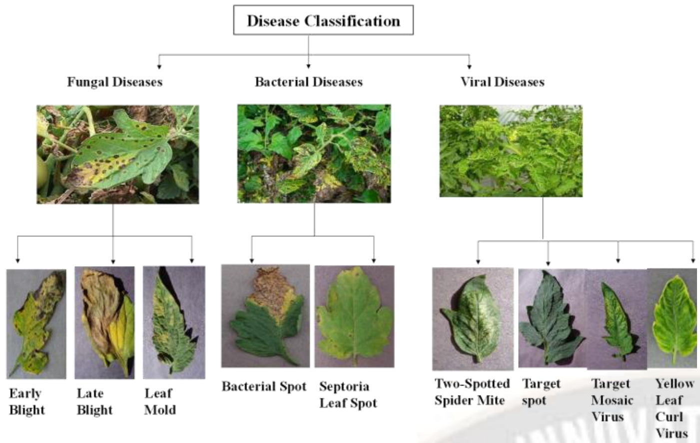

Figure 1Tomato Plant Leaf Diseases Sample Images

III. CLASSIFICATION OF DEEP LEARNING TECHNIQUES

Deep Learning is a type of machine learning that uses a three-layer architecture, with an input layer, an output layer, and a hidden layer, to process information in a manner analogous to the human brain when dealing with complex and large datasets.

Artificial neural networks (ANNs) are the backbone of deep learning algorithms and their brain-like information-processing capabilities make them useful for early disease diagnosis. similar to self-learning training machines, during the training phase, algorithms utilize unknown components in the input distribution to extract features, classify objects, and discover significant data patterns. Deep learning made use of many models. While there is no such thing as a perfect network, a problem-specific algorithm is used to determine the most efficient means of improving feature generation.

To detect the forecast plant diseases different DL algorithms are applied. DL is the best choice than machine learning for convolution for huge data, disease detection, and classification utilizing CNN networks such as LSTM, RNN, GAN, and others which have the highest accuracy rate. The deep learning algorithms are divided into categories depending on the different neural network methods listed below as shown in Fig2.

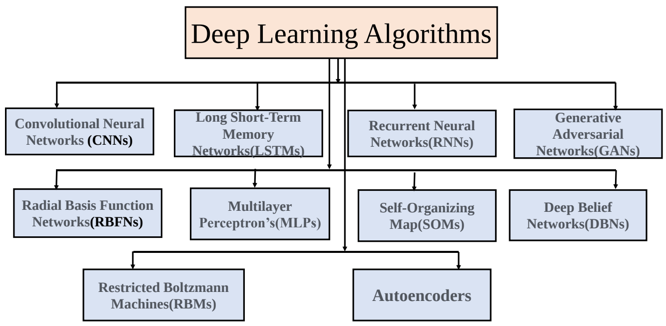

Figure 2 Deep Learning Algorithms Classifications

A. *Convolutional Neural Networks (CNN)*

T CNNs are a special kind of neural network that specializes in processing images and other data that can be represented on a grid. To describe it simply, a digital image is a binary representation of visual data. The pixels are generally stored in a grid, and their values specify the colors and intensity of each yellow circle. CNN is a multi-layer neural network that is used for object recognition and image processing, as well as detecting time series and animal image detection, extracting features from data as shown in Fig3 [75-127].

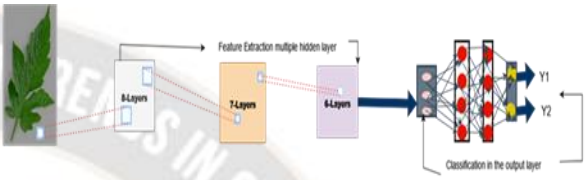

Figure 3Convolutional Neural Networks (CNNs)

B. *Long Short-Term Memory Networks (LSTMs)*

LSTM networks were created to solve the long-term dependency problem of RNNs Feedback connections distinguish LSTMs from feedforward neural networks. LSTMs may handle complete sequences of data (e.g., time series) by preserving important knowledge about past data points to help process future data points as shown in Fig4. Thus, LSTMs excel at processing text, speech, and time-series sequences [75-127].

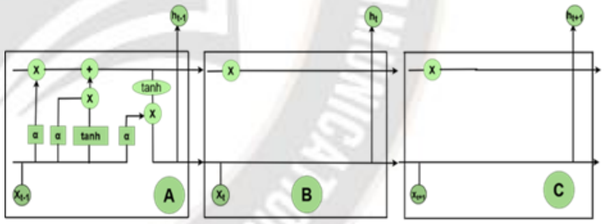

Figure 4 Long Short-Term Memory Networks (LSTMs)

C. *Recurrent Neural Networks (RNNs)*

As the most common type of neural network and widely considered the most effective, Recurrent Neural Networks (RNNs) are at once the most fundamental and the most powerful. These algorithms have been receiving a lot of attention since they have shown potential in a range of innovations. RNN was developed with the goal of improving the processing of sequential data as shown in Fig5 The concept of internal memory is what sets RNN apart from other neural network types [75-127].

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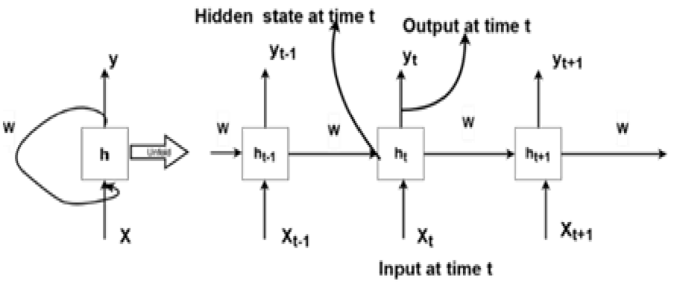

Figure 5 Recurrent Neural Networks (RNNs)

D. Generative Adversarial Networks (GANs)

In the field of deep learning, generative adversarial networks, often known as GANs, are a specific kind of generative algorithm that is utilized to generate new data that is comparable to the training data. A GAN consists of a generator that learns how to generate fake data and a discriminator that learns how to recognize such data. Together, these two components learn how to detect fake data as shown Fig6.

GANs have grown in popularity over the years. For the study of dark matter, they can mimic gravitational lensing to improve scientific imaging. Visuals in older games can be improved by utilizing GANs and image training to create 4K or higher resolutions of the original 2D graphics [75-127].

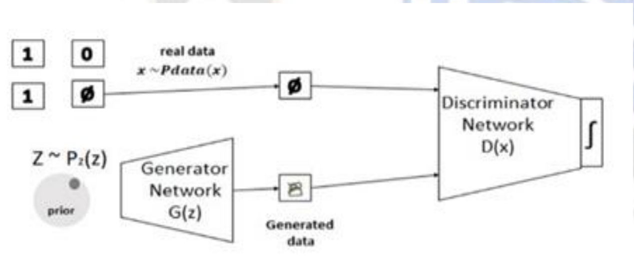

Figure 6 Generative Adversarial Networks (GANs)

E. Radial Basis Function Networks (RBFNs)

When compared to other types of neural networks, the structure of radial basis function (RBF) networks is unique. Many layers of a neural network's architecture are typically used to make non-linearity through the iterative application of nonlinear activation functions. By contrast, an RBF network has only three layers: input, hidden, and output. In an RBF network, the input layer just acts as a channel for data to be passed on to the hidden compute layer. The strength of an RBF network lies in its hidden layer, where computations take place in a way that is fundamentally distinct from those of other neural networks. It is the job of the output layer to make predictions, either through classification or regression as shown Fig7.

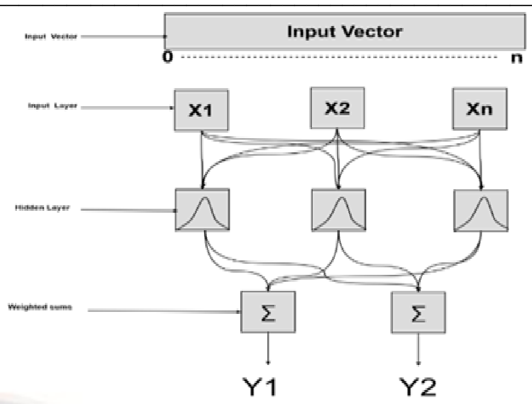

Figure 7 Radial Basis Function Networks (RBFNs)

F. Multilayer Perceptron's (MLPs)

The perceptron excels at the task of categorizing data that can be neatly split into linear categories. As the XOR example showed, they encounter serious limitations when working with data sets that do not even follow this pattern as shown Fig8. The XOR problem is an example of a set that cannot be partitioned linearly into any four-point classification.

However, in order to categorize datasets that are not simply divisible by linear measures, the Multilayer Perceptron, often known as MLPs, is able to circumvent this problem. That is because they utilize a more robust and complex architecture to create regression and classification models for challenging datasets.

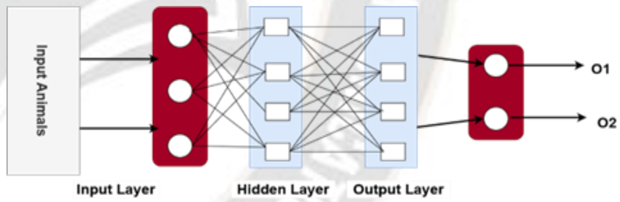

Figure 8 Multilayer Perceptron's

G. Self-Organizing Maps (SOMs)

As with many types of modern Classifiers, the Self Organizing Map (also known as a Korhonen map or SOM) is based on biological models of neural systems from the 1970s. It uses a competitive learning method to train its network in an unsupervised manner. To simplify difficult problems for human comprehension, SOM is employed in clustering and mapping (or dimensionality reduction) techniques to map multidimensional data onto lower-dimensional spaces as shown Fig9. The Input layer and the Output layer are the two components of a SOM.

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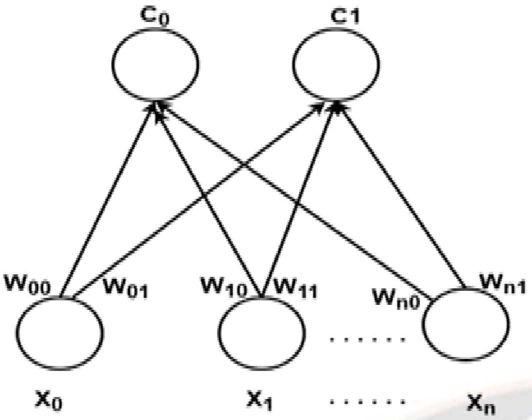

Figure 9 Self-Organizing Maps (SOMs)

H. Deep-Belief-Networks (DBNs)

In the field of deep learning, DBN is an unsupervised probabilistic algorithm. DBN is made up of several different layers of unpredictable predictor variables. A binary set of variables, often known as feature detectors or hidden units, are the subject of this study. DBN is a hybrid graphical model that can generate new data as shown in Fig10. Both uppermost layers are completely agnostic. Directional links from higher levels to lower ones.

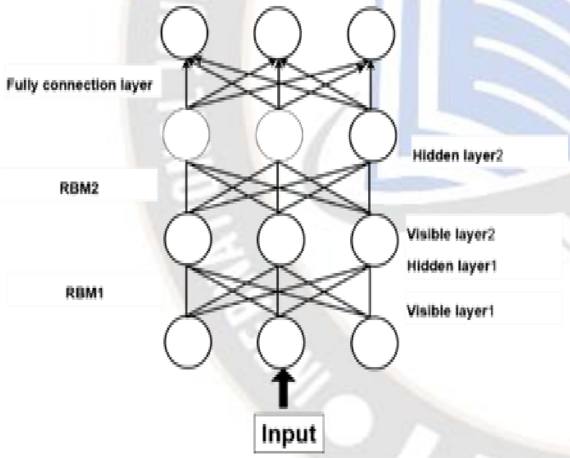

Figure 10 Deep Belief Networks (DBNs)

I. Restricted Boltzmann Machines (RBMs)

Essentially, it is a set of interconnected neural nodes. There are two layers in this device: the input/visible layer and the output/hidden layer. The v-symbolizes the top, visible layer, while the h-symbolizes the bottom, hidden layer. It is important to note that the Boltzmann machine does not have an output layer. Boltzmann machines are a special kind of generative and random neural network that can represent and (in sufficient time) solve difficult cooperative and productive problems as shown in Fig11.

The visible and concealed units of RBMs are separated into two categories. Every visible and concealed unit is connected. When using RBMs, all the visible and hidden units are connected to a single bias unit.

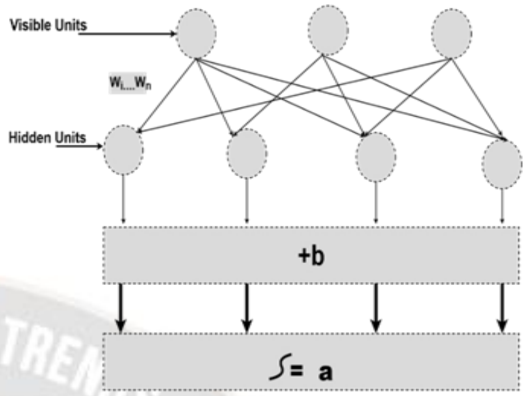

Figure 11 Restricted Boltzmann Machines

J. Autoencoders

The input and output of an auto encoder are identical, making it a sort of feed forward neural network. As a result, they can reconstitute the output after compressing it into a lower-dimensional code. The code, also known as the latent-space representation, is a condensed version of the input.

Each part of an autoencoder the encoder, the code, and the decoder has its own specific function. Data is compressed and a code is generated by the encoder; the decoder uses this code alone to reassemble the data as shown in Fig12.

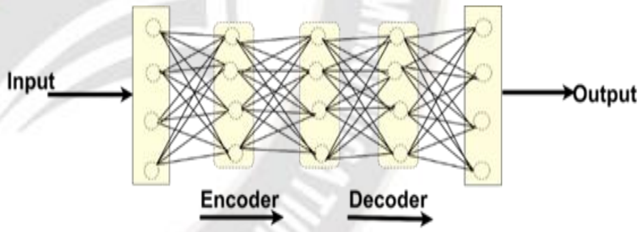

Figure 12 Autoencoders

IV. SUITABILITY OF CNN FOR TOMATO LEAF DISEASE DETECTION

Their primary distinction is that, in comparison to conventional feedforward neural networks, they require a much smaller number of structural parts (artificial neurons) due to the layering process they employ. Several CNN baseline architectures have been created for use in image recognition applications, and these have been effectively used to challenge visual imaging challenges.

A rise in popularity for Deep Convolutional Neural Networks can be traced back to the 2012 ImageNet challenge when the Alex Net architecture significantly improved accuracy on the classification job by decreasing top 5 errors by an additional 8%. Alex Net's unique ideas contributed greatly to speed gains when compared to LeCun's original architecture [128-165].

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Recently, Deep Learning has emerged as the go-to strategy for problems of this nature. According to Brahimi et al., deep learning techniques (using Alex Net and Google Net architectures with pre-trained weights) outperformed traditional machine learning approaches when it came to the classification of 9 diseases affecting the tomato plant [18-165].

An application of feed-forward neural networks known as convolutional neural networks (CNN) [38] has been developed to automate the process of finding and diagnosing diseases that can affect tomatoes. There are multiple stages to this, each of which is tailored to a particular purpose. Layers in Convent are composed up of neurons arranged in all three dimensions (x, y, and z) . Furthermore, the neurons in a given layer do not have a one-to-one connection with all the neurons in the layer below, but rather, they have connections with only a lazed subset of those neurons [128-165].

These days, Deep Learning is the go-to method for making precise diagnoses of plant diseases. Diseased leaves are gathered and categorized. Additional data is gleaned from the labeled images when they are pixelized . With the help of automatic feature extraction, neural network models can classify images automatically into categories. Following feature extraction, the most informative features are narrowed down to a manageable number, and then one of several classification methods is employed [128-165].

In deep learning, the convolutional neural network is a powerful Algorithm for overcoming the identification problem. Recently, CNN has emerged as the self-learning model capable of feature extraction and image classification CNN has shown promising results in a variety of uses, including author identification, object detection, text detection from images water leakage detection, biological image analysis, and facial image detection [57-165].

CNN has its own system for learning feature extraction and labeling, which it uses to better understand images. Numerous fields have benefited from employing CNN, with better results being achieved in each one. This includes object detection, scene text detection, biological image analysis, and face recognition. [CNN] [App for CNN] Since CNN considers regional background information from around the world, it can infer more robust features. Significant differences on key elements that emerged as a result of shadows, distortions, and brightness oscillations in natural photos can also be addressed thanks to image processing methods. The light, clouds, and other environmental elements could all contribute to the subtle but noticeable differences shown in natural images [57 -165].

The application of the convolutional neural network (CNN) Algorithm for the analysis of plant leaf images has progressed to the point where CNN algorithms can be successfully applied to leaf disease analysis due to their increased sensitivity to important features. This is possible because CNN algorithms take into account more information. One of the many areas in which it has recently demonstrated great success is in the identification of plant diseases [57-165].

To summarize, deep learning is an approach to training neural networks to do novel tasks. The ability of deep learning to automatically extract data from images is a major benefit. As it is trained, a neural network learns to extract features like these from the data. The most popular deep learning model right now is the multi-layer feed-forward neural network or CNN.

V. CNN MODELS FOR TOMATO LEAF DISEASE DETECTION

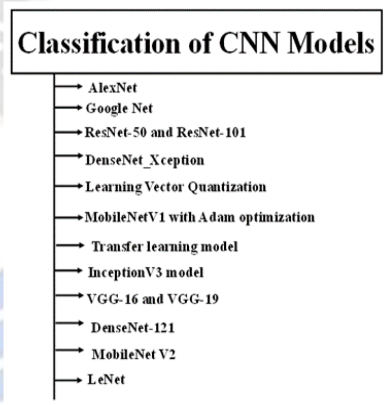

Figure 13 Classification of CNN Models

Convolutional neural networks (CNNs) are a subset of deep learning algorithms that have been designed to handle pixelated data. These networks are widely used in image recognition and analysis. It receives an image as input, applies a set of biases and weights that it has learned to each image, and then uses this information to tell them apart. One potential benefit of adopting CNN is that it requires far less pre-processing than previous algorithms meaning the neural network learns on its own instead of relying on filters that were manually constructed for traditional methods [63-175].

To extract characteristics from high-dimensional data, convolutional neural networks (CNNs) are a type of artificial neural network. In this Analysis, a max-pooling layer is added to a simple CNN model consisting of three convolutional blocks. In addition, a dropout layer, a dense layer, and a flat layer were added as a conclusion as shown Fig13. The function that flattens the pooled feature maps into a single vector before sending them to a dense layer comes in between the pooling and dense layers [63-175].

A CNN-based DL model was built to distinguish between healthy and TSW-afflicted images. The CNN-based model can binary and multi-classify the image collection. It has two convolutional (C) layers, two max-pooling (M) layers, one flattening (F) layer, and one fully connected (D) layer. Train the two convolutional layers with an input image to extract features using convolution [. The max-pooling layer receives the output

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feature vector next. This layer pools feature vectors from convolutional layers and finds the maximum value from each feature map batch [63-175].

A. Google Net

The GoogleNet can save time in part by reducing the size of the input image while keeping the relevant spatial details intact. Several filters were applied to the publicly available Plant Village dataset to highlight the disease hotspots using GoogleNet CNN architectures. For the purpose of measuring performance and contrasting the two well-known CNN designs, we used the P, R, F1, and OAI measures across three different situations (color, grayscale, and segmented). Results showed that GoogleNet was superior to Alex Net [6-180].

B. ResNet 50 and ResNet 101

ResNet-50 is a 50-layer deep convolutional neural network. The network can be loaded in its pre-trained state, which has been exposed to over a million images in the ImageNet database [16]. The ResNet-50 model is the basis for this 97% accurate framework. Advantages include a trained model that can improve its results by augmenting them with additional data. Cons It might be pricey to maintain a high-configuration hardware environment for training purposes [28-97].

The ResNet-101 network has 101 hidden layers of processing power. In order to save time, you can simply load a version of the network that has already been trained with data from the ImageNet database of over a million images. Mask R-CNN improves detection rate and performance with ResNet-101, reaching 99.64%mAP. Promptness and accuracy in implementation are two advantages [16-186].

C. DenseNet_Xception

The network is trained on high-level parameters using an image of a tomato illness, then used to classify nine tomato leaf varietals. High-level network parameters are updated while low-level parameters remain unchanged during training. Average accuracy and specs vary. The best recognition accuracy of Dense Net Xception is 97.10 percent, but its parameters are at most, and the best recognition accuracy of Shuffle Net is 83.68 percent, but its parameters are small, providing model support for the continued development of an intelligent tomato disease diagnosis system based on smartphones and other mobile terminals, which is crucial for pest control decision-making [5-135].

D. Learning Vector Quantization

Using the RGB channels from images of tomato leaves in the Plant Village dataset, how model trained a convolutional neural network model. Due to its topology and adaptive model, the Learning Vector Quantization (LVQ) model was our top pick for classifiers Kohonen designed a neural network called Learning Vector Quantization, which blends unsupervised learning with competitive learning. It is a robust heuristic technique for resolving categorization issues. LVQ's adaptable model and straightforward topology have led to its widespread implementation. It divides the input data into a predetermined set of categories. Specifically, it has an input layer, a Kohonen (competition) layer, and an output layer. The neurons in the input layer tally the input values.

The neurons in the output layer each stand for a specific type of input. Full connectivity exists between the input and Kohonen layers, while only a partial connection exists between the Kohonen and output layers. Kohonen's learning layer is where things get done. The classified information is then sent to the linear output layer [73-185].

E. MobileNetV1 with Adam optimization

As of late, lightweight deep neural networks with low latency have been developed by using depth-wise separable convolutions. Due to its lightweight and low-latency nature, the MobileNetV1 architecture is well-suited for edge device applications like mobile and embedded vision. Clinical diagnosis of tomato leaf diseases: inductive learning. No further training data was used as MobileNetV1 trained using a batch size of 32, a learning rate of 0.0001, and 15 epochs, each of which has 199 steps, to achieve a 99% accuracy. An Adam optimization strategy was used to achieve this [26-165].

F. Transfer learning model

After a transfer learning model confirmed the presence of disease, absolute color was added to the image. Absolute colour space is a visual space that preserves color accuracy across a wide range of brightness. This method helps smooth the transition from the non-standard RGB colour profile to the device-independent XYZ colour profile. The ICC input profile must include a Matr value. To characterize a device's colour characteristics or viewing demands, the International Color Consortium (ICC) defines a mapping between the device's source or target colour space and a profile connection space (PCS) [9-138].

G. InceptionV3 model

In this work, we employ Neural Computing Stick (NCS) to expedite computation and simplify detection because of their mobility, speed, and accuracy. To detect Septoria leaf spot disease in tomatoes, researchers at Intel NCS used the InceptionV3 model to create a deep learning system [14-147].

H. VGG-16 and VGG-19

A classifier based on the deep learning algorithm VGG (Visual Geometry Group)16, which includes 16 convolutional layers in its network. improved upon the Alex Net model by proposing

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this deep CNN version. Multiple smaller convolution filters, such as 33, are used by VGG16. To better learn complicated features from training data, use smaller kernel stack filters. We have observed the classified various tomato leaf diseases using a pre-trained VGG16 model.

Because VGG16 is a pre-trained model of the convolution Neural Network, we can infer that it provides superior performance and accuracy. CNN pre-trained model (VGG16) helps improve model accuracy and performance. While there are certain benefits to employing this model, there are also some drawbacks, such as the model's relatively high price tag and the increased complexity that comes with having more parameters [33-197].

Transforming a network that has already been trained using transfer learning saves time and effort compared to starting from scratch. It does not need a load of information or processing power. The ability to apply one's understanding of one problem type to another. VGG19 enables a pre-trained network to be applied to the task of learning something new. The network has already been trained on a huge number of characteristics, which can be used effectively for new classification tasks [38-184].

This paves the way for re-training with the updated information. Since overfitting is undesirable and large changes to pre-trained weights can compromise previously extracted features, we opted for a slow learning rate in the fine-tuning phase. was developed by the Visual Geometry Group at Oxford University specifically for the 2014 ImageNet Large Scale Visual Recognition Challenge [38-184].

I. DenseNet-121

Though all the models did well, the DenseNet-121 model had the highest accuracy while also being the smallest in size. DenseNet-121's results were similarly achieved by ResNet-101 and VGG16. However, ResNet-101 was much bigger, making it inappropriate for mobile devices with limited storage space. Additionally, this research can be expanded to identify and diagnose diseases, and a lightweight model can be implemented for use on mobile devices. A better dataset can lead to better results [29-199].

J. MobileNet V2

Methods based on transfer learning and the SSD Mobile Net V2 Finite 640x640 model are utilized to detect plant diseases. Our final decision was since this model's power source would be most conveniently located at the base of the vertical pole. A voltage converter, also installed on the same vertical pole, is used to deliver power to the Raspberry Pi, the servo motors, and the limit switches [34-199].

The model uses a depth-wise convolution of (3x3) and a point-wise convolution of (1x1) instead of a single, continuous convolution layer. This change improves efficiency by a factor of eight to nine, at the expense of a little amount of precision. To save representational power, non-linearities are also eliminated from the thin layers, and linear bottlenecks are employed instead. displays the architecture of MobileNetV2 with a dense network output [41-199].

K. LeNet

The input and kernel sizes, the number of filters, and the convolutional layers of a CNN are all determined by its architecture. If you want an example of a simple NN, look no further than LeNet or LeNet-5, both of which accept a (32x32) input. Alex Net is an eight-layer NN, while VGG-16 has 16. More layers in a network means more complexity and more time to train [18]. The activation function is either Sigmoid or Tanh, and the pooling is averaged. Roughly 60,000 parameters make up this network [18-139].

VI. REVIEW ON CNN MODELS

In this Analysis, we observed the performance of many different CNN architectures for disease detection in tomato plants, including Dense Net, VGG-19, and ResNet. In both the experimental results and comparison analysis sections, it is shown that the Dense Net model has the best average validation accuracy for detecting tomato leaf diseases while using a reduced number of epochs than the other models and recognizing the gradient vanishing problem. Below, we describe our findings from a comparison of the different CNN models' authentication accuracy for the detection of 10 distinct diseases of tomato leaves in Table 1,2,3. The following Graph summarizes together the results of a comparison study into the accuracy of various CNN models.

Table 1 for Data for training and Testing with respect to the 80 and 20 ratio.

S.NO	**Model**	**Accuracy (80-20)**	**TOTAL IMAGES**
1	DenseNet_Xception	97.1	41263
2	LeNet	98	18378
3	CNN	95	16011
4	VGG-19	97	16000
5	DenseNet-121	99.69	14529
6	InceptionV3 model	95.85	3362
7	MobileNetV1 with Adam optimization	99	1432
8	Resnet-50	98	1000
9	Learning Vector Quantization	90	500

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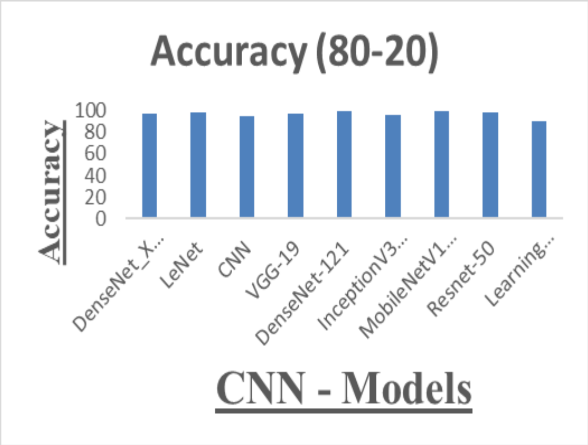

Figure 14 Performance Measurements of various CNN Models with ratio of 80 and 20.

This comparative analysis has been clarified in a Table 2 and Figure 15 Graph for accuracy in different CNN models' processing of data, with 70% and 30% respectively presented below.

Table 2 for Data for training and Testing with respect to the 70 and 30 ratio.

S.NO	Model	Accuracy (70-30)	TOTAL IMAGES
1	CNN	92	22930
2	MobileNetV2	97.26	18601
3	CNN	98.77	11804
4	VGG16	99.23	10735
5	GoogleNet	98	10735
6	Transfer learning model	99.386	400

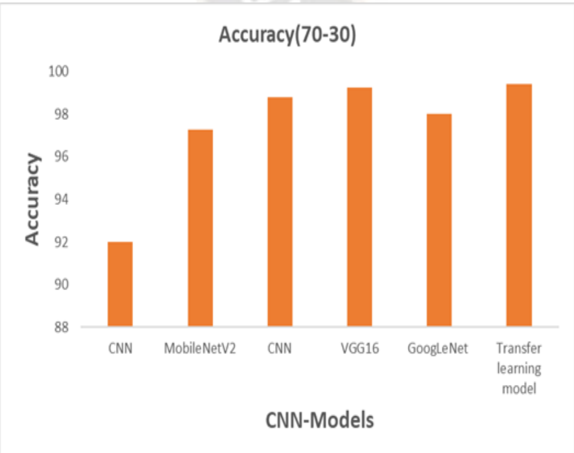

Figure 15 Performance Measurements of various CNN Models with ratio of 70 and 30.

This comparative analysis has been clarified in a Table 3 and Figure 16 Graph for accuracy in different CNN models' processing of data, with 60% and 20% respectively presented below.

Table 3 for Data for training and Testing with respect to the 60 and 20 ratio.

S.NO	Model	Accuracy (60-20)	TOTAL IMAGES
1	CNN	98	87840
2	LeNet	97	55000
3	VGG16	95.5	33000

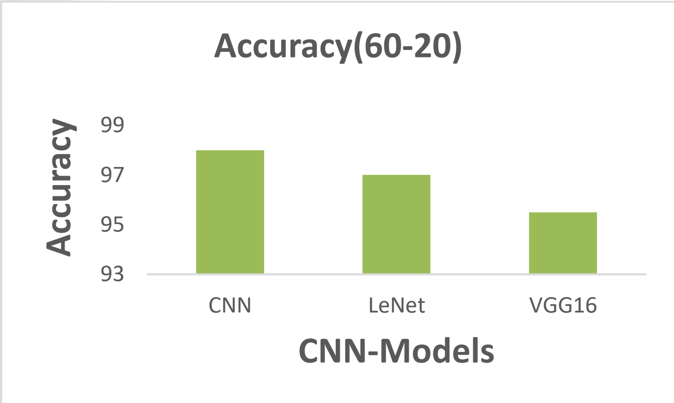

Figure 16 performance measurements of various CNN Models with ratio of 60 and 20.

VII. CONCLUSION

Deep learning and image categorization are currently used for various applications in the agricultural field aiming at quality and productivity. CNN is great for image recognition and classification in deep learning. Most farmers struggle to prevent crop diseases and fungus or bacteria attacks. If done appropriate and on the right time, the gain in agricultural yield will be noticeable. Deep CNN models identify and classify diseased tomato plant leaves. Tomato leaf disease affects crop quality, despite expensive fertilizers and hence farmers must worry about plant diseases every other day. By identifying the symptoms, the proposed approach may detect tomato plant diseases early. Various CNN architectures—Alex Net, LeNet, GoogleNet, VGGNet, ResNet, and Dense Net were compared for tomato plant disease identification performed on a plant village data set. The accuracy achieved varies from 90% to 99% and can be improved further. The results from a genuine image collection are encouraging. Both experimental findings and comparative analyses demonstrate that the Dens Net model has the highest average validation accuracy for detecting tomato leaf diseases with the most epochs and resolving the gradient vanishing problem. In conclusion, we could very well accept Dense Net model detects tomato plant diseases more efficiently than any other existing models.

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