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AUTOMATED TOMATO LEAF DISEASE DETECTION TECHNIQUE USING DEEP LEARNING

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ABSTRACT

Artificial intelligence is the most common and comprehensive common-sense cognitive engine in the ecosphere. Essentially affluent are both the cloud SaaS business model and the concept of an AI business platform. Early infection detection is one of the most efficient ways to keep plants healthy in a complicated environment since it links to artificial intelligence (AI) systems that can communicate with other digital systems. Plant disease detection has been digitized and data-driven with the growth of smart farming, which could make decisions automatically and intelligently, as well as smart analytics and management. This is as a result of continuous developments in computer vision. Due to AI-based ML and DL, the area of digital image processing has recently made tremendous strides. Researchers are interested in learning more about how to employ a good machine learning or deep learning model to identify plant ailments because when pests attack plants and crops, it has an impact on the nation's agricultural productivity. Farmers or specialists will often utilize their unassisted eyes to detect and identify plant disease. But this method could be costly, time-consuming, and incorrect. Automatic detection using image processing techniques yields rapid and reliable results. This study investigates a unique approach to classifying Tomato leaf images using deep neural networks and building a diagnostic model for plant illness. As computer vision research and development broadens and improves accurate plant protection, the market for computer vision applications in precision agriculture may grow. the creative teaching techniques, methodology, and approach enable for a quick and simple system installation in this article. The automated plant disease detection method's data collecting, segmentation, feature extraction, and classification phases are also detailed.

Keywords: *Plant Disease Detection, Artificial Intelligence, Machine Learning, Agriculture Automation,*

1. INTRODUCTION

The backbone and one of the most important industries in our country is agriculture. The majority of Indians are more inclined to choose agriculture as their line of work. [1] India is the second most productive country in the world in terms of agriculture. Up to 70% of India's rural areas are supported by agriculture, which makes a considerable economic contribution to the country. Further, it approximately contributes 17% of the nation's GDP and employs nearly 65 percent of the overall population. The production of almost all sorts of crops, fruits, and vegetables in warm to subtropical climates and soil conditions is referred to as farming. The overall productivity of these crops can be increased due to the durability of their roots and leaves. As per the report generated by the Food and Agriculture Organization (FAO), the total productivity of agriculture should rise up by around 70% till 2025 so that the increasing demand of food can be fulfilled [4]. In another report generated by the FAO, it was stated that since the year 2014, the total number of people suffering from hunger is rising continuously at the slower pace. According to

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current projections, almost 690 million people are starving which accounts for 8.9% of the global population. These statistics has risen by 10 million in a year and are about to rise to 60 million in 5 years. Diseases, pests, and some other unwanted components that occur in harvests can influence agricultural production to plummet. The influence of these toxic components on agricultural products is directly proportional to the quality of crops and total loss. The terminology "pesticides" was established to counteract, regulate, and minimize the impacts of diseases on production [5]. determined. Diseases, however, typically impair the output of these crops because of the changing dynamics of the environment [2]. The illness that affects plant leaves and destroys crops is brought on by a variety of circumstances. This has a detrimental effect on the economy of the nation. 90% of the world's population currently relies on agriculture. 80% of the food consumed worldwide is produced, but sadly, over 50% of that food is lost to plant infections and pests [3]. Additionally, if these illnesses are not identified at the right time, it might result in food insecurity. The use of pesticides is considered as the viable option for preventing these diseases from infecting crops and for improving the overall productivity. Since, the year 1950, farmers are using pesticides which acted as the major driving force behind the increasing food production which in return allows us to meet the increasing food demand. However, the continuous use of such compounds causes several disadvantages that affect the environment system. The use of such chemicals has a detrimental effect on biodiversity especially insect, bird and fish populations. In addition to this, the quality of soil, air, and water also gets affected with the excessive use of pesticides. Their usage also poses a significant health hazard to human life as they can cause acute as well as chronic diseases. Pathogens are responsible for inducing diseases in plants and they do it under different environmental conditions. The symptoms of the disease infected plants usually appear on its leaves, stem and fruits. Plant disease are usually caused by the biotic organisms or abiotic substances. Different types of biotic disease are caused by fungi, bacteria and viruses. Whereas, some Diseases are carried on by abiotic substances like hail, spring frosts, dynamic weather conditions, chemical combustion and so on. These diseases are non-communicable, less dangerous and can be prevented often [6]. Whether the plant diseases are caused by biotic or abiotic conditions, it is considered as one of the leading causes for damaging the crop yield that ultimately leads to agricultural and economic losses. As a result, it is critical to recognize and detect the diseases in plants in earliest stages so that the productivity is not affected. Over the last few decades, many plant disease detection methods were proposed for precise agriculture practice.

1.1 Current Detection Systems and Issues Associated

Early detection of plant disease is crucial to ensuring a safe and abundant production. Traditionally, these diseases were detected through manual process where the structure, appearance and other properties of the plant leaves were analyzed for detecting the diseases [7]. Many farmers lack the necessary professional skills and have low educational backgrounds. Because of this, it becomes quite difficult for them to detect and identify the disease which leads to inaccuracy and productivity and economic losses [8]. One of the most employed approaches for detecting the plant is visual based inspection where an experienced person identifies and detects the plant disease with the naked eye. This necessitates a huge staff of professionals as well as ongoing experienced observation, both of which come at a great cost whenever crops are vast. Simultaneously, in other nations, growers lack adequate infrastructure or perhaps even the kn0wledge of how to approach professionals. As a result, consulting specialists is both expensive and time- Consuming [9]. Therefore, this process is complex, ineffective and inappropriate and hence need for automating the detection process arises. A novel technique for precisely identifying plant diseases has been developed as a result of the development of computer vision in recent years. Over the years, a substantial number of AI based ML and DL approaches have been developed for detecting diseases in plants effectively and efficiently. Several ML techniques like, “clustering, Decision Tree, K-nearest neighbor, Support vector machine, Naïve Bayes” and so on have been implemented by various experts in their models for predicting the diseases in plants at earliest stages. However, the problem with such ML algorithms is that they provide effective results only under limited and constraint setups. Moreover, the traditional ML algorithms were not able to handle large and complex datasets and undergo through overfitting problems. Therefore, the researchers moved towards the Deep Learning approaches which include, CNN, RNN, LSTM, Bi-LSTM etc. For generating more effective and precise results. The DL methods can effectively handle large and complex datasets and overfitting issues. With advancements in hardware mechanics, deep learning approaches are being used

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to tackle complicated issues in a short amount of time. However, DL approaches necessitate a large volume of data for providing superior outcomes for diagnosing plant disease. This is a disadvantage because most currently accessible databases are tiny and don not possess enough high-quality images A feasible and appropriate database should include images that are taken under different circumstances. If there are not enough samples in the training data, the classification accuracy rate of standard DL approaches is not up to the mark

2 LITERATURE REVIEW

The authors in [10], employed the image processing along with the ML approaches in order to detect and identify the diseases in plants. The authors collected the standard pictures from number of plants for validating their method. Initially, they segmented and separated the diseased part of the given input image and then the data was mined for a number of features. attained ROI. Moreover, for classification purpose, the SVM technique was used. The experimental findings showcased that the suggested model was able to detect plant diseases with high accuracy and classification rates. The researchers in [11]proposed a vision based automated plant disease identification system wherein they utilized the image processing techniques. They recognized the color feature of the plant leaf and then K mean algorithm and GLCM algorithm were utilized for color segmentation and categorizing leaf infection respectively. This approach showed effective performance and results. The research in [12] focused on detecting diseases like "Leaf blight, Black rot, stable and Black measles in grapevines". Several ML based approaches were proposed for detecting diseases in grapevines; however, no one had yet proposed a detection technique that could detect all four diseases. The algorithm was made using the images that were gathered from the plant village dataset which would assist in training the Efficient Net B7 deep architecture using transfer learning. The features that were then obtained were down-sampled using an approach known as logistic regression (yes or no based on the observation data). The suggested model was able to detect diseases in grapevines with an accuracy of 98.7 percent. Similarly, the researchers in [19] used Extreme Learning Machine (ELM) along with a single layered feed-forward neural network for identifying different plant diseases by analyzing leaf images In the suggested scheme, the feature images served as the input which were alter on pre-processed by using the HSV color space and after this important and crucial feature were extracted by using the Hara lick textures. The extracted characteristics were then used to train and evaluate the ELM classifier. After the testing was completed, the ELM precision was computed. The dataset utilized was a subset of the Plant-Village dataset made up of tomato plant leaves. When c0mpared to other models such as the SVM and Decision Tree, the ELM's results indicate a higher rate of accuracy of 84.94 percent. The authors in [20] suggested an effective agricultural disease's detection technique based on computer vision and ML techniques such as RF algorithm. The suggested algorithm worked with a 93 percent accuracy rate and could detect up to 20 distinct diseases in five standard plants. The authors in [21]focused on developing an improved disease detection model in which they utilized computer vision and ML methodologies The presented method worked by taking a leaf's raw image and retrieving properties such as shape, color, texture, vein, and so forth by preliminarily processing and separating. After that the leaf image was categorized using a variety of ML classifiers like RF, SVM, K-Nearest Neighbor and ANN. In comparison to other classifiers, the suggested prediction model performed well with RF. The scholars in [22] studied transfer learning and deep feature extraction models to evaluate CNN architectures. SVM and KNN were the two classifiers that were used to classify all the features retrieved. The utilization of the open-source "Plant Village Dataset" made all this work possible. The study in [24] focused on using image processing and ML algorithms to access and diagnose plant infection as monitoring plant diseases by hand at every step was very challenging and demanded more labor and time. Using edge and colour-based image processing algorithms, plant disease symptoms were recognized and separated.

Table 1. ML based Accuracy

Authors	Classifier	Feature extraction	Accuracy
[13]	SVM	Color histogram	Achieved high results in terms of precision and Recall
[14]	Random for-est	Centered log ratios (clr)	Accuracy 80 percent
[15]	Machine learning models	NA	93Percent

[16]	SVM	Shape and texture features were Ex-tracted	97.2percent
[17]	SVM	Ten shape features, five texture features	93.5 percent
[18]	SVM	K-means clustering for segmentation	high accuracy
[28]	ANN and BPNN	Otsu thresholding and k-means form segmentation and color co-occurrence and leaf color for extracting features	High classification accuracy

The type of disease was classified using a multi-class SVM based on appropriate features collected from the separated diseased leaf section. plant diseases brought on by different pathogens, including viruses, bacterium and fungus were investigated in this study in order to detect plant diseases early and on a regular basis. The study in [25] focused on diseases detection technique using ML and image processing tools. The algorithm worked in steps firstly by discovering and capturing the diseased region followed by preliminary processing of picture and then the separated parts were acquired and the area of concern was identified and feature extraction was performed. Lastly, to receive the findings, the received results were transmitted through SVM Classifiers. The task of disease categorization was surpassed by SVMs, and the findings revealed that the methodology proposed in this paper produced considerably better results than before utilized disease identification systems. The study in [26] discussed how Categorization was used to reduce losses in agricultural product yield and amount; however, if thorough analysis was not done in this strategy, It may have severe effects on plants, affect product quality and productivity. Plant disease grouping was crucial for sustainable agriculture. Manually monitoring and treating plant infection was quite tough since it demanded a large quantity of effort and a long processing period hence Image processing was employed for the detection of plant infections. Loading leaf images, preliminary processing, segmentation, feature extraction and classification through SVM Classifier were some of the stages involved in leaf disease categorization. authors in[27] presented a unique web enabled diseases detection system termed as WEDDS which was established on compressed sensing to spot and categorize infection in leaves. For the separation of the sick leaf, a statistically established thresholding technique was given.

The segmented leaf's CS measurements were sent to the cloud to simplify storage. At the overseen location, the measurements were obtained and the features were derived from the reconstructed separated picture. For categorization and inspection, an SVM classifier was utilized.

The suggested WEDDS' accuracy had been evaluated and contrasted with previous methods. Additionally, tested on a Raspberry Pi 3 board was the WEDDS. According to the findings, the recommended strategy had overall detection and classification accuracy rates of 98.4 percent and 98.5 percent, respectively. A method of disease diagnosis for rice plants using image processing techniques was suggested in the study in [28]. An image segmentation and feature extraction method was used to research the illness. Specifically, brown spot disease and paddy blastwere the subjects that were mostly investigated, and SIFT was utilised to extract shape and colour information. According to the results, a 95 percent accuracy was attained by employing an SVM classifier following feature extraction. Using image processing techniques and the SVM classifier, the researchers in [29] [13] concentrated on creating an automated disease diagnosis approach for pomegranate leaves. Colour "image segmentation" with the "K-means clustering algorithm" was used to extract the desired region from the picture of a pomegranate leaf. Additional noteworthy texture and colour properties were extracted from the target region with the intention of training the SVM classifier. Two feature sets, "Entropy and saturation" and "Hue and Energy set," were classified. Using SVM in conjunction with the findings showed that The categorization was carried out with better accuracy using "entropy and saturation" characteristics, etc.

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Table 2. [29]Comparative Analysis Of Classifiers And Feature Selection Methods

"Feature selection method"	"Number of features Selected"	"Classification Method"	"Accuracy"
None	700	SVM	80%
PSO (Particle Swarm Opti-mizations)	91	KNN	Accuracy 75%
GSA (Gravitational Search Algorithm)	87	SVM	85%
Spider Monkey Optimiza-tion	84	LDA	71%
Exponential Spider Mon-Key Optimization	82	KNN	81%

2. METHODOLOGY OF PROPOSED WORK

In order to understand the clear picture of proposed study's flow, the below given figure give the overview of proposed design and its various modules. Model: Phase 1The figure 1 depicts the framework inside the intended scheme that will work on designing a model that will assist the overall system to extract multi domain features selection of qualitative feature set. These qualitative information set is expected to be effective in extracting valuable pattern from input images, and improving the detection system's accuracy or detection rate. The first and foremost step is to analyze and conduct the literature review so that the process of plant diseases can be understood theoretically and conceptually, specifically in the light of AI based ML and DL. After this, the next step will be to determine the shortcomings and limitations that are found in current approaches. The performance of different approaches will also be analyzed by comparing them with each other. Based on the findings obtained from the literature, problem statement, work scope and objectives will be defined in the research. In the next phase of research, the design and development of proposed plant disease detection model is defined. The dataset used, tools and appropriate methodology will be explained briefly in this phase so that an effective model is developed. In addition to this, flowcharts, algorithms, and mathematical models will also be provided for gaining a clear view of developed model. In the next step of research, the dataset used for detecting the plant diseases will be processed and important and crucial features will be extracted from it. Once the fea- tures are extracted, feature selection technique will be implemented for reducing the dimensionality and complexity of the dataset so that its overall efficacy is enhanced. Fifth step will involve executing various experiments with the proposed model to evaluate and analyze its effectiveness. Also, the results obtained for the proposed technique will be c0mpared with the similar traditional approaches in terms of various performance metrics.

The sixth phase is to test and evaluate numerous performance characteristics, as to conduct a comparative evaluation of the proposed and current systems. Lastly, the total research would be written and polished for publishing in a systematic way, stressing the designed algorithms, observations, tests performed, and results in order to demonstrate the effective attainment of the intended objectives. Figure 1 shows the proposed framework, which has a feature extraction and feature selection model. In the previous research, it was absent. By using this model, we can select important features that will be very useful in identifying plant leaf disease.

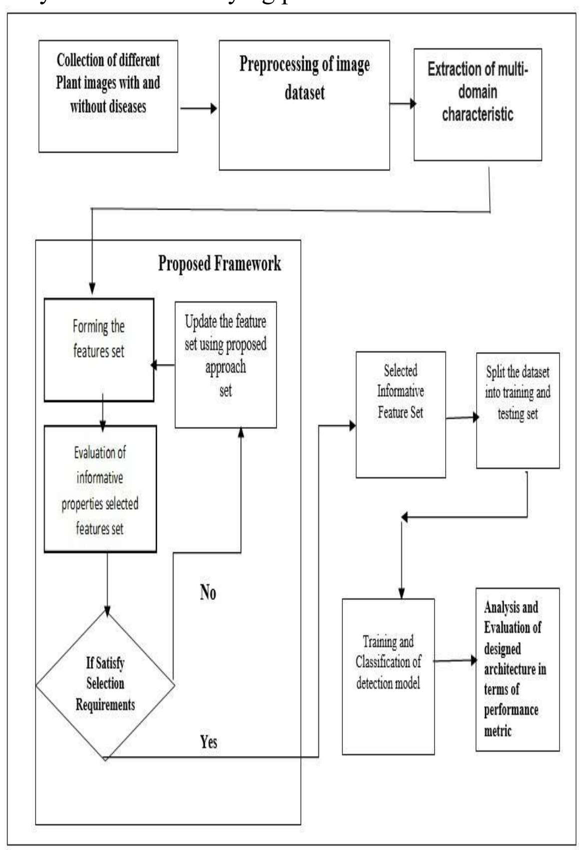

Figure 1. Proposed Framework for Phase of Selecting Qualitative Information Set

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Dataset: Vegetable plants include tomato plants. Food is cooked using it. We consume a lot of tomatoes every day. Farmers put a lot of work into growing tomatoes, which are grown on farms. If a disease is not treated in a timely manner, it might kill plants. Therefore, we will develop a model that can forecast tomato plant illness. They have a variety of plant disease datasets available, but I just picked the tomato dataset because I am planning to create a model for a tomato plant.

4. POSSIBLE OUTCOMES

The suggested plant disease detection model is supposed to provide a reliable source, an efficient and workable model that not only finds plant diseases in their earliest stages but also addresses the problems with the existing disease detection models. In addition, it is anticipated that the suggested classification accuracy rate model would have a much higher accuracy rate than the conventional methods for detecting plant diseases. An overview of the existing plant disease detection systems, their datasets, methodology, and limitations may be used to summaries the overall results that will be reached. Large datasets may be handled by a highly accurate and trustworthy plant disease detection model, which significantly decreases processing time and complexity an enhanced model for detecting plant diseases

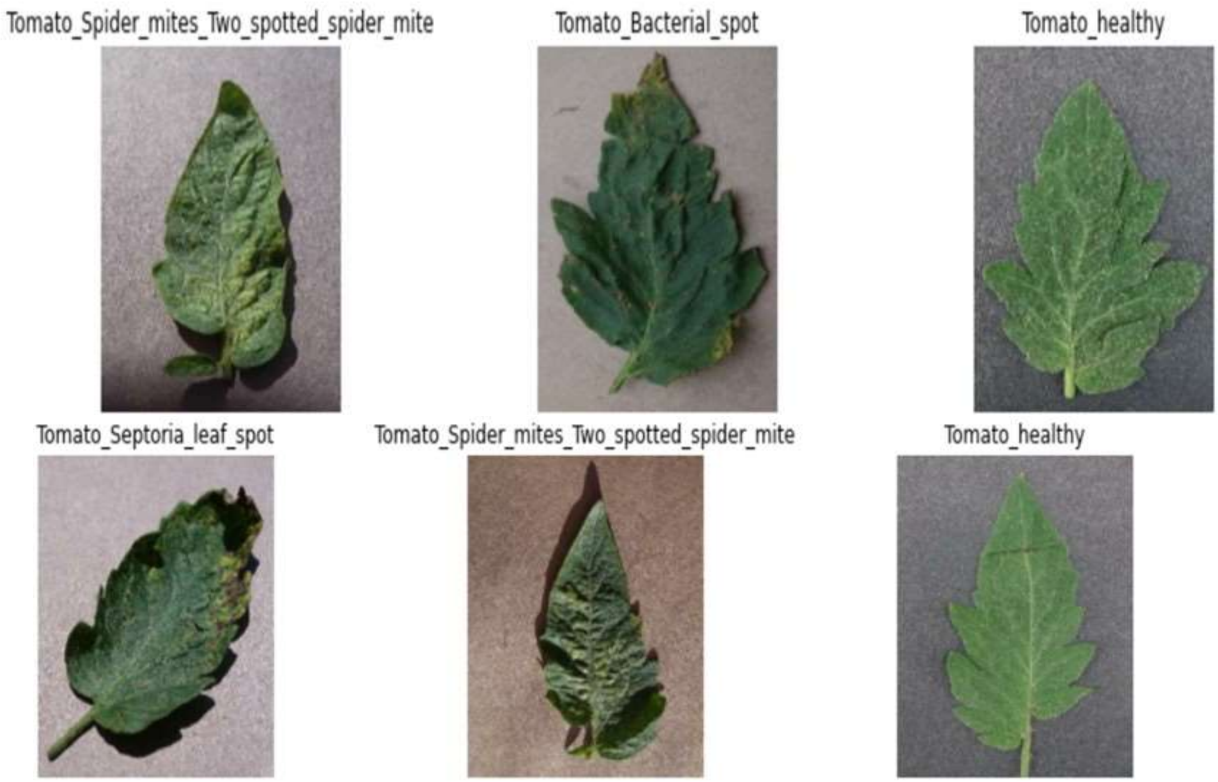

Figure 2. Infected And Healthy Tomato Leaves

in which classification accuracy rate is higher than existing plant disease detection approaches. Improvements in detection rate and other performance dependency factors.

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In Figure 4, the epoch value and the accuracy value are compared. If the epoch value goes up, the accuracy will also go up. But at some points, the accuracy value goes down. The reason behind this is that at the time of training, when we are splitting the value into train and test phases, it is evident that some parameters are not evaluated, so during testing, some untrained parameters show the lowest accuracy because we are splitting the dataset into train and test part randomly

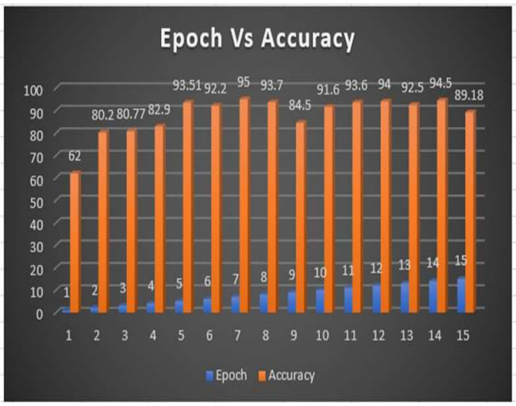

Figure 3. Epoch vs Accuracy

5. COMPLETE CONNECTION

The next phase is to integrate convolutional neural networks with artificial neural networks. From here, creating a convolutional neural network becomes more difficult and

sophisticated. The traits that we retrieved in the earlier rounds are present in this vector. We first employ two thick layers and then employ a sigmoid activation function for binary classification. The CNN classifiers seen in Figure 5 are defined by Table 2, and they employ four Convolution layers, four max-pooling layers, the sigmoid function to activate the neurons, and fully connected layers to predict whether a leaf is healthy or sick

We first employ two thick layers and then employ a sigmoid activation function for binary classification. The CNN classifiers seen in Figure 5 are defined by Table 2, and they employ four Convolution layers, four max-pooling layers, the sigmoid function to activate the neurons, and fully connected layers to predict whether a leaf is healthy or sick. When compared to a model that is constructed from scratch, a pre-trained model has lower accuracy. It is doing significantly better than the pretrained model with an accuracy rate of 89. The comparable bar charts are shown in figure 6 below. Additionally, it has been noted that the suggested model requires less storage space than the pretrained model.

Figure 4. CNN Classifiers

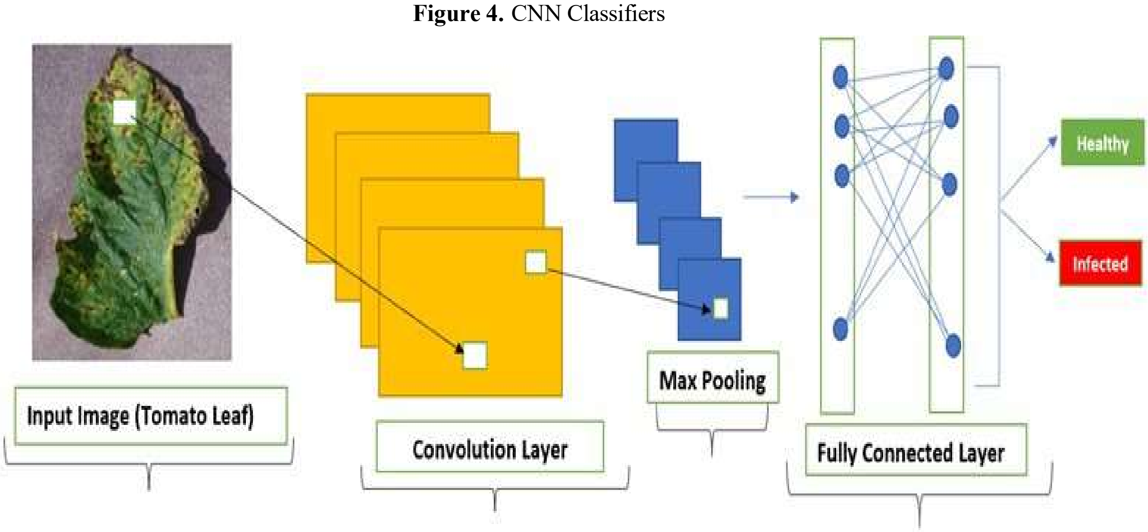

Table 3. Hyper-Parameter For Convolution Neural Network

Hyperparameter	Description
No of Convolution Layer	4
No of Max Pooling Layer	4
Drop out Layer	0.5
Activation function	sigmoid
Learning Rate	0.0001
No of Epoch	15
Batch size	32

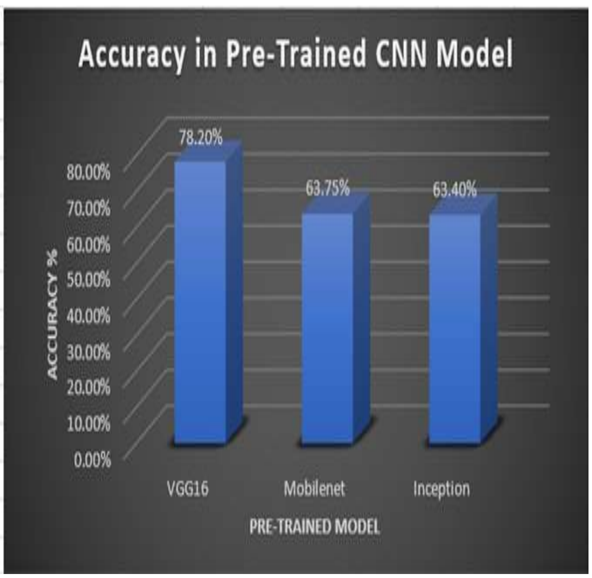

Figure 5. Accuracy of Pre-Trained Model

Our dataset was used to produce the training set and the test set. Eighty percent of the data in our dataset are in the training set, while the remaining twenty percent are in the test set. In order to construct the validation, set of data, certain images from the test set and training set were taken. A mistake in the training set of data is known as training loss. We receive an error after running the validation batch of data through the trained network. The problem is referred to as validation loss. Train and validation mistakes are reduced with increasing epochs. As train loss and validation loss reduce, train accuracy and validation accuracy eventually rise. "Fig. 7 displays training accuracy vs. validation accuracy and training loss vs. validation loss."

6. RESULT

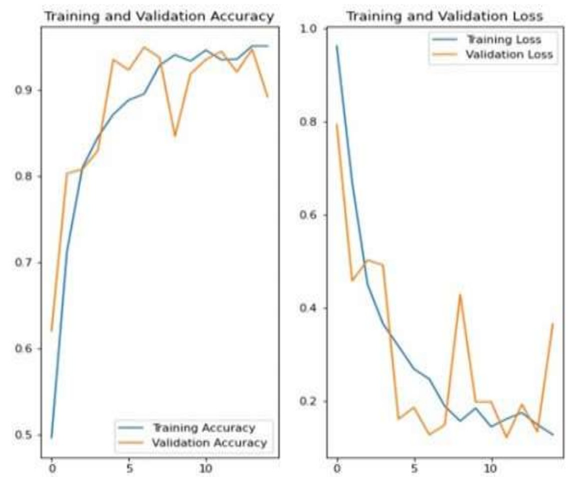

Figure 6. Training and Validation Accuracy, Training and Validation Loss

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Table 4. shows the predicted result after training the model with a high confidence level. If a new image dataset is fed into the model, the model will respond with accuracy. It shows that the accuracy level of the model goes up in some cases and goes down in others.

Actual Disease	Predicted Disease	Image	Confidence Level
Tomato Leaf Mold	Tomato Leaf Mold		75.28%
Tomato Septoria leaf Spot	Tomato Septoria leaf Spot		99.15%
two Spotted spider mite	two Spotted spider mite		99.62%
Tomato Septoria leaf Spot	Tomato Septoria leaf Spot		100%

The predicted confidence level for tomato leaf mould is 75.25%. The accuracy of two spotted spider mites is 99.62%, and the forecast level for tomato septoria leaf spot is 99.15%. Therefore, tomato leaf disease might be predicted using this model.

First, we used a neural network to train the model. In order to get the prediction, we feed in a fresh image dataset, and our model finds the disease with reasonable accuracy.

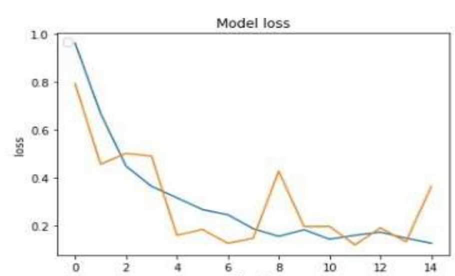

Figure 7: Model loss

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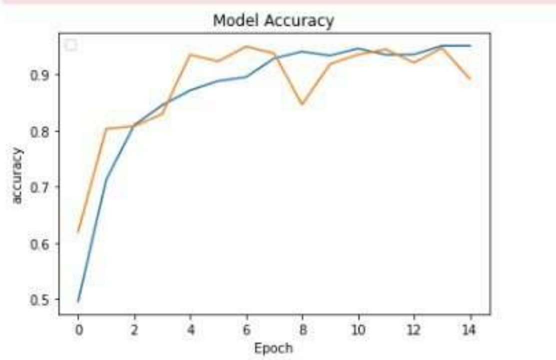

Figure 8: Model Accuracy

Figure 7 & Figure 8 Shows model loss and model accuracy performance of model varies along with training parameters After the experiment, it is found that as the epoch increases, the loss will be decreased. The model also performs well when the epoch is high and it shows good accuracy level

6. LIMITATION:

Plant diseases have long been a major issue in agriculture. By making the best judgements possible based on the outcomes of DL techniques, precision agriculture has enabled early disease identification and the reduction of losses. Recent developments in DL offer solutions with extremely precise findings, and readily accessible technology makes processing quick. The decision-making procedure, nevertheless, may be enhanced. The models that are now available perform poorly when evaluated under actual circumstances. In response to this, and considering the authors' prior work, a unique strategy for plant disease detection was put out in an effort to get through the primary obstacles to practical application. In this study, a brand-new dataset was presented. It includes pictures of leaves in actual environments, shot from various perspectives, and labelled for both classification and detection tasks. By doing so, the dataset is by doing this, the dataset is widened, which raises the model's classification precision and practical applicability.

7. CONCLUSIONS

Accuracy is one approach to assess a classification model's efficacy. Typically, it is expressed as a percentage. Accuracy is defined as the number of forecasts when the expected and actual values match. It is binary (true/false) for a particular sample. Although accuracy is usually graphed and tracked throughout the training process, it is frequently related to the overall or final model accuracy. Accuracy is easier to comprehend than loss. A loss function, often called a cost function, takes into consideration the likelihood or uncertainty of a forecast based on how far off the forecast is from the real value. This gives us further details regarding the effectiveness of the model. Loss is the opposite of accuracy is not a percentage but the total number of mistakes produced for each sample in the training or validation sets. To get the "ideal" parameter values for the model (for example, the weights in a neural network), loss is frequently utilized during training. The goal of the training process is to lower this number. The two most prominent loss functions, cross-entropy loss and log loss, yield identical results when computing error rates between 0 and 1. This study presents a deep learning method for categorizing several varieties of succulent tomato plants using the CNN model. Five max-pooling layers and four convolutional layers are used to construct our network model. Each totally connected layer is essential to contain a dropout layer in order to lessen over fitting in the system. Data augmentation techniques including rotation, shifting, scaling, shearing, and flipping are used to improve the dataset. After successfully completing 15 epochs, the model achieves 89% accuracy on the dataset. Here, three classes of succulent plants have been analyzed, however this is insufficient for model optimization or presents a problem for further, undiscovered succulent species. As a result, our long-term objective is to raise the number of users for better optimization.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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