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Tomato Leaf Disease Prediction using Neural Networks

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***Abstract*— Tomatoes, which are extensively grown in Indian agricultural fields, are among the commonly cultivated vegetable crops. The tropical climate in India provides favorable conditions for tomato cultivation. However, various factors, including climatic conditions and other elements, can adversely affect the normal growth of tomato plants. Plant diseases present a significant risk to crop production and can lead to economic losses, adding to the challenges posed by climate conditions and natural disasters. Unfortunately, traditional methods of detecting diseases in tomato crops have proven to be ineffective and time-consuming. This study primarily aims to accurately identify tomato plant leaf diseases that are found using image analysis. Various methods have been applied for extracting the features that have been used to improve the accuracy of classification. Alex Net, InceptionV3, and a CNN (Conv Net) algorithm have been utilized to classify many types of tomato plant diseases. When comparing the results, it is notable that the CNN (Conv Net) classifier outperforms the other two models. The findings demonstrate the practical applicability of the model in real-life scenarios.**

***Index Terms*— CNN, Tomato Plant Diseases, Machine Learning, Deep Learning, Artificial Intelligence**

I. INTRODUCTION

Plant diseases pose a significant crisis in the agricultural sector, hindering agricultural development and resulting in substantial economic losses for farmers. Tomato, being a staple crop in India, is cultivated extensively across the country. Detecting and identifying tomato leaf diseases solely through naked-eye observation by agricultural experts is a challenging and less accurate task, which is only feasible for limited areas. Farmers and agriculturalists face difficulties in accessing agricultural experts, and the inspection of crops by these experts requires significant financial investment and consumes a considerable amount of time.[16] However, the recent advancements in the domain of technology have given rise to technologies like AI and ML. These technologies facilitate the automatic detection of tomato plant diseases detected on leaves using computerized techniques, enabling the monitoring of large-scale tomato crops in a more efficient manner. Many of the researches have proven that over 20 varieties of tomato diseases negatively impact the yield and quality of tomatoes, leading to substantial economic losses for farmers. These diseases affect various parts of the tomato plant, including leaves, roots, fruits, and stems, often resulting in abnormal growth, discoloration, damage, and ultimately plant destruction. Some common plant diseases found in tomato include early blight, spider mites, leaf Mold, target spot, yellow curl virus, and mosaic virus as depicted in Fig 1.

Timely detection of tomato diseases is crucial for minimizing the impact on plant health and maximizing crop yield. A number of methods that have been proved to be innovative have been used for the identification and the detailed classification for specific plant diseases. The main goal of this study is to provide farmers with accurate

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identification of diseases in their early stages and raise awareness about these conditions. By doing so, farmers can take proactive measures to mitigate the spread and negative results of the diseases on tomato plants, ultimately improving crop yield.[18]

Noteworthy progress has been made in the field of detection of leaf diseases in plants through the application of AI, and ongoing research continues to explore new avenues. Various techniques such as Machine Learning, Deep learning, Artificial Neural networks, Convolutional neural networks, and others have been employed to go through this topic. Machine learning, subset of AI is playing a major role in enabling systems to learn and enhance their performance over time.

Recent invention in the domain of deep learning and neural networks have led to improved classification accuracy in plant disease detection. A cutting-edge technique involves utilizing deep learning with Neural Network, which incorporates multiple stages of feature extraction automatically, resulting in enhanced classification accuracy. There are many different methods in machine learning but, C CNN has gained wide popularity and has shown notable superior performance compared to traditional classification methods.[17] The introduction of state-of-the-art meta-architectures such as VGGNet, LeNet, ResNet, AlexNet, Squeeze Net, ImageNet and others in Deep CNN has further contributed to significant improvements in predicting tomato leaf disease, achieving the high classification performance.

The results of these CNN models have inspired many researchers to adopt pre-trained models for the detection of tomato diseases detected through leaves. In the specific context of tomato plants, a growing research interest in utilizing CNN for disease detection. Convolutional layers are major part of CNN, which consist of sets of filters are applied to images to generate feature maps or images, along with additional layers such as pooling. Through the iterative process of convolution layers and other processing layers in classification of images, the feature maps are extracted, ultimately leading to the network producing a label that represents an approximate class, shown in Figure 2.

Fig 1. Instances of Tomato Leaf Diseases

II. Related Works

Alvaro Fuentes et al introduced an innovative approach for object detection, which combines the Faster R-CNN, R-FCN, and SSD algorithms with the state-of-the-art deep CNN feature extractors. Their proposed model, known as R-CNN with VGG-16, demonstrates enhanced recognition capabilities. Notably, this model effectively reduces false positives during the training phase, improving overall accuracy. Accuracy of 92%. However, one the potential improvement of this project model could have been increase in performance speed.[1]

Halil Durmas et al proposed the utilization of Deep Learning Network-based architectures, specifically squeeze Net and AlexNet, for the recognition of tomato leaf diseases. The results indicated that AlexNet achieved a higher classification accuracy of 95.65%. One advantage of using squeeze Net is its lightweight nature, which demands lower computational resources. The factors associated with squeeze Net include longer training times and the requirement of smaller batch sizes while the training process of model [2]

Melike Sardogan et al presented a novel approach that combines a CNN with the LVQ (Learning Vector Quantization) algorithm for leaf disease recognition. The proposed method resulted in classification accuracy of 86%. The key advantage of this study is the ability to achieve early and effective recognition of plant leaf diseases. However, important thing to note is that one of the potential factors to work on this method is the challenge related with the classification rate [3].

The authors of (Arnal Barbedo, 2019) segmented images into separate spots and lesions, which increased image number and data diversity as well as made it feasible to recognize numerous diseases in the same leaf, where single symptoms were being considered. About 12% accuracy was achieved, which is greater than the case when usage of raw images was done. The authors of (Arnal Barbedo, 2019) used a pretrained CNN that employed Google Net

architecture to study the use of separate spot and lesions, instead of using whole leaves and classified various plant infections. They concluded that the accuracy attained from separate lesions and spots was 94% [4].
Akshay Kumar et al put forth CNN-based architectures in their research. Among the proposed models, VGGNet exhibited exceptional performance and achieved an impressive accuracy of 99.25%. One notable advantage of this model is its ability to reach the maximum accuracy while also minimizing computational loss. However, it is worth mentioning that training VGGNet demands a significant time and necessitates a high-end hardware setup, which can be thought of as a potential improvement of the approach in future [5]
Elhassouny et al have introduced a mobile application that is built using deep CNN for identifying diseases in plant leaves. Derived from the "Mobile Net" CNN model, this application demonstrates the capability to point out the ten most common leaf diseases. The dataset used for the application consists of 7176 tomato leaf images. Notably, the proposed application achieves an impressive diagnostic accuracy of 88.4% that meets the necessary speed requirements. This mobile application provides an accessible and efficient tool for diagnosing tomato leaf diseases on the go. But small dataset used during training can be improved to make it more functional [6].
Ireri, D et al employ an RBF-SVM classifier that utilizes LAB color-space pixel values to effectively detect infected areas of tomato plants. The classifier focuses on identifying bruises on the stalk and calyx of infected tomato plants, while also categorizing tomatoes as either healthy or infected. The authors developed 4 different machine models for grading cases that have been on basis of color and texture data. Among these models, the RBF-SVM consistently outperforms the others, exhibiting an impressive accuracy of 95.15% for the healthy and infected tomato classes.
Interestingly, accuracy achieved by the classifier for identifying healthy and diseased tomatoes improves as the class number used in grading increases. This highlights the classifier's efficacy in distinguishing between various grading categories [7].

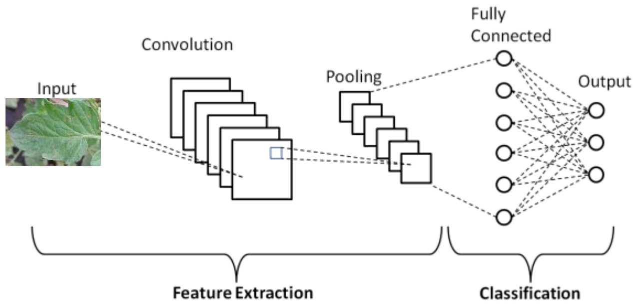

Fig 2. Convolutional Neural Network

Karthik R. et al introduced a CNN-based methodology that attained a commendable accuracy of 98%. This approach offers the advantage of a higher detection rate compared to existing methods, showcasing its efficacy in accurate classification. However, training model on a significantly large dataset can improve the thoughts on novelty of this CNN technique [8].
Surampalli Ashok et al presented a CNN-based methodology that achieved an impressive accuracy of 97%. One notable advantage of this study is its high performance in accurately classifying data. However, it is notable that the utilization of recent algorithms and classifiers may be necessary to reach optimum results, indicating a potential implementation for future of proposed methodology. It is important to explore and leverage the most up-to-date techniques for optimal performance [9]
Agarwal has et al introduced a straightforward CNN-based model for detecting nine different disease types in tomato plants. The model
comprises eight hidden layers and is evaluated using the dataset from Kaggle, which includes 18,160 leaf images categorized into ten classes. For training, 1400 images from each class are used, while 100 images are used for testing and 300 images for model validation. The model achieves an impressive accuracy of 91.2% over the Plant Village dataset.
To further enhance accuracy, the authors augment the dataset by incorporating processes such as flipping, rotation, and random variation of leaf intensities. This augmentation results in an increased accuracy of 98.4%. Notably, the proposed machine model has shown greater performance compared to classical machine learning processes and pre-trained models across various datasets [10].

Lee, J. et al introduce a system that combines AI and image techniques for processing for multi-class identification and instance-based segmentation to assess the size and mass of fruits captured in image. The conclusion of their study demonstrates a notable correlation between fruit size and mass, indicating that AI techniques can effectively capture this intricate physical relationship for predicting ultimate mass of the fruits. Alex net algorithm is used. The authors evaluate various AI methods and establish that the estimated mass aligns closely with the actual mass. The experimental findings reveal an impressive detection accuracy of 99.02%, highlighting the system's ability to accurately estimate fruit mass based on size information [11].

Rong, J et al present a two-phase approach for accurately locating the plant disease of cherry tomatoes. The first phase involves utilizing a YOLOv4-Tiny detector to quickly identify the approximate location of the tomatoes in real-time. In the second phase, the peduncle and fruit pixels are segmented using YOLACT + +. The resulting peduncle mask is then used for curve fitting, enabling the discovery of three key points that form a geometric framework for predicting the peduncle posture.

The proposed method achieves an impressive accuracy rate of 92.7%, demonstrating its effectiveness in accurately identifying and predicting the posture of cherry tomato peduncles. [12].

In their research conducted by Naresh K. Trivedi et al., study is done while making use of Google Colab and a dataset consisting of 3000 photos of tomato leaves affected by nine different diseases, along with healthy leaves. The entire procedure involved several steps. Firstly, the input photographs were pre-processed to enhance their quality, and the specific images related to the diseases of interest were identified. Subsequently, the original photos were divided into multiple regions to facilitate further processing. At this stage, the CNN model was fine-tuned, adjusting its hyperparameters to extract additional patterns from the data, such as colors, texture, and edges. The conclusion of this study demonstrated that the model achieved an accuracy of 98.49%.

This experiment serves as evidence for effectiveness of applied methodology in accurately classifying and diagnosing leaf diseases in leaves. The combination of Google Colab, a large dataset, and careful preprocessing techniques contributed to high accuracy achieved by the machine learning CNN model [13].

In a recent study conducted by H. Kibriya et al. in 2021, tomato plant disease detected on leaves classification was addressed using two CNN-based models, namely Google Net and VGG16 with 96% accuracy. The researchers employed deep learning process to handle the challenge of accurately detecting tomato plant leaf diseases. Their study aims to detect an efficient way to solve this problem. The testing of the models were done on the Kaggle dataset, which consists of 10,735 leaf samples.[14]

Study conducted by Ashqar, Abu-Naseer and Abu-Naser, et al in 2019 was done on Plant seedling dataset, they pre-processed input images by resizing them to 128x128 pixels, normalizing the pixel values to a [0,1] range and balancing dissimilar classes.

The authors selected a CNN (Conv Net-based) approach for classifying plant images with dataset containing approximately 5000 images belonging to 12 different species and achieving accuracy of 99.48%.

TABLE I MODEL ACCURACY COMPARISON

Authors	Methodology Used	Performance Metrices
Fuentes, Alvaro	Faster R-CNN, R-FCN and SSD algorithms, VGG-16	92%
Durmuş, Halil, Ece Olcay Güneş, and Mürvet Kırcı	Squeeze Net and Alex Net	95.65%
Sardogan, Melike, Adem Tuncer, and Yunus Ozen	CNN and LVQ	86%
Arnal Barbedo, J. G	CNN (Google Net)	94%
Kumar, Akshay, and M. Vani.	VGG Net	99.25%
A. Elhassouny and F. Smarandache	Mobile Net	88.4%
D. Ireri, E. Belal, C. Okinda, N. Makange, and C. Ji	RBF-SVM	95.15%
Karthik, R	CNN	98%
Ashok, Surampalli	CNN	97%
M. Agarwal, S. Kr. Gupta, and K. K. Biswas	CNN	91.2%
J. Lee, H. Nazki, J. Baek, Y. Hong, and M. Lee	Alex Net	99.02%
J. Rong, G. Dai, and P. Wang	YOLOv4	92.7%
N. K. Trivedi, V. Gautam, A. Anand, H. M. Aljahdali, S. G. Villar, D. Anand, N. Goyal, and S. Kadry	CNN	98.49%
H. Kibriya, R. Rafique, W. Ahmad and S. M. Adnan	VGG16 and CNN	96%
Ashqar, Abu-Nasser and Abu-Naser	CNN (Conv Net)	99.48%

Transfer learning means the process of reusing a pretrained model for solving a new problem that is different from scratch, which involves learning or training data from basic. [15]

In this literature survey, we have conducted a comprehensive evaluation of researches that made use of Machine Learning for tomato plant disease identification. We have compared the findings from various published models and observed that CNN demonstrates high accuracy in disease identification when trained on sufficient data. It was also found in the survey that ConvNet has shown highest accuracy performance. Our Findings and their accuracy are depicted in Table I

III. METHODOLOGY

A. Image Acquisition

Involves obtaining online images that are to be used as input data for the purpose of training and also testing machine learning models. Image acquisition involves capturing or retrieving pictures from various sources, like cameras, sensors, or databases. We acquired our images from Kaggle dataset

B. Image Pre-processing

Once the image has been acquired, if they are deemed unsatisfactory or the regions of interest are not clearly defined, image preprocessing processes can be employed to mitigate noise and enhance the quality of the picture. Image preprocessing encompasses several ways such as cleansing, integration, transformation, and reduction, all aimed at improving the overall clarity and utility of the images. These techniques to reduce noise, enhance features, adjust color or contrast, and prepare the images for subsequent analysis or processing steps are used.

Pre-processing means steps taken to prepare image data before feeding it into the neural network. The main goal of pre-processing is used for quality improvement of the input data, reduce noise, and help the neural network to better understand and extract useful features from the images. For our study, the entire dataset is divided into 80% train data and the 20% test data. Rescale is a pre-processing step where the pixel values of the input images are rescaled by dividing each pixel value by 255. This helps in normalizing the pixel values to a range between 0 and 1, which can improve in the training of the model which is performed in our research.

C. Image Segmentation

Segmentation means the process of dividing an image into distinct parts based on shared characteristics or similarities. The goal of image segmentation is to isolate specific regions of interest within the image that possess similar attributes. By employing image segmentation techniques, we can extract only the relevant portions of the image that exhibit the desired characteristics, while disregarding irrelevant details in the entire image. This makes it possible for more focused analysis and processing on the specific areas of interest, leading to more accurate and efficient interpretation of the image data. In our research for image segmentation

1. Data Augmentation

Data augmentation is important technique in training neural networks for prediction of diseases in leaves. It involves generating new training samples by applying various transformations and modifications to the existing dataset. By augmenting the data, the network becomes exposed to a wider range of variations, enhancing its ability to generalize and recognize diverse patterns that are related with the disease. These transformations can include rotations, translations, scaling, flipping, brightness adjustments, contrast changes, and adding noise. By applying such variations to the images, the neural network can learn to be robust to changes in lighting conditions, image orientations, and other factors that may change the appearance of disease.

2. CNN Architecture

a. Alex net

AlexNet is a powerful neural network. It is of eight layers,that include five convolutional layers and then followed by three fully connected layers. It takes a fixed-sized RGB image, typically 224x224 pixels. The convolutional layers use various filter sizes, strides, and padding. The first layer has a filter size of 11x11 with a stride of 4, while the subsequent layers use smaller filter sizes of 3x3 or 5x5 with a stride of 1.

After each convolutional layer, max pooling reduces the resolution of feature maps. ReLU activation functions are applied to introduce non-linearity after each convolutional layer and fully connected layer. Soft max layer processes the learned features from the convolutional layers is used for image classification into various classes. final layer applies the soft max activation function to produce class probabilities. It assigns probabilities to each class label, indicating the likelihood of the image given as a input belongs to a particular class.

b. InceptionV3

InceptionV3 is a deep learning architecture that combines CNN with inception modules. The initial layers of InceptionV3, called the stem, perform basic extraction of features and dimensionality reduction. An Inception block captures feature at different scales by using parallel convolutional filters of different sizes. InceptionV3 employs multiple Inception blocks stacked together to form a deep architecture. It also has reduction blocks that reduce the spatial dimensions of feature maps while increasing the channel numbers. At the top of the network, fully connected layers are being used for the final classification. These layers process the learned features and produce class predictions. In InceptionV3, there are typically two fully connected layers followed by a soft max layer for multi-class classification.

3. CNN (Conv Net) algorithm

The CNN (Conv Net) algorithm is a specific type of CNN model architecture commonly used for image classification tasks. It is designed as a sequence or linear stack of layers, where the output of one layer serving as input to next layer. CNN (Conv Net) algorithm consists of following layers stacked one after another. Convolutional layers apply convolutional filters to the input volume to detect specific patterns or features. Then activation layers and pooling layers down sample the feature map’s spatial dimensions. Following these layers fully connected layers are used for classification, as they map the extracted features to the class labels and make the final predictions. Soft max, is used to the find the output of the last fully connected layer to produce class probabilities, indicating likelihood.

4. ReLU

ReLU (Rectified Linear Unit) is a commonly used activation function in neural It introduces non-linearity and aids to the network learn complex relationships between input features. ReLU sets negative values to zero, allowing positive values to pass through unchanged. By enabling the network to learn non-linear mappings, ReLU enhances the model's ability to capture intricate patterns and features associated with plant diseases. With its effective representation learning capabilities, ReLU contributes to improved accuracy in classifying plant images and predicting the disease

5. Residual Block

The Residual Block is the building block in neural networks. It consists of multiple layers, including convolutional layers, batch normalization, and non-linear activation functions. The key feature of the Residual Block is the introduction of skip connections, which allow the network to learn residual features. These skip connections enable the direct flow of information from first layer to next, bypassing intermediate layers. The Residual Block captures both shallow and deep features, enhancing the model's ability to extract relevant information from images. The residual learning within the block enables the network to focus on learning the change between input and output, improving the network's performance.

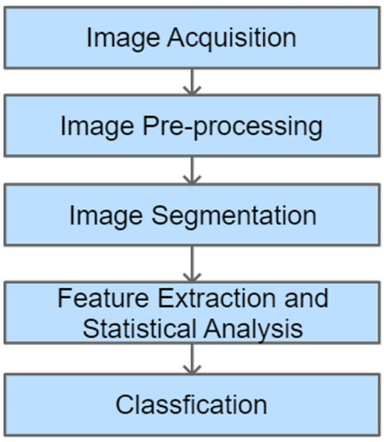

Fig 3 Procedure of Leaf Disease Detection

6. Maxpool 2D

MaxPooling2D is a commonly used pooling operation in neural networks. It reduces the spatial dimensions of feature maps, preserving the most salient information. By partitioning the input into non-overlapping regions, MaxPooling2D selects the maximum value within each region, discarding less relevant information. MaxPooling2D aids in extracting robust and invariant features from plant images, allowing the network to focus on essential patterns. It helps to achieve translation invariance, making the model more robust to slight shifts in the input.

7. Flatten

The Flatten operation is a crucial step in neural networks. It transforms multi-dimensional feature maps into a one-dimensional vector. By flattening input, network can connect all the extracted features to fully connected layers for further processing. This operation enables the network to capture global patterns and relationships among features. The flattened representation allows for efficient information flow and parameter sharing in subsequent layers. By reducing spatial dimensions, the Flatten operation helps to mitigate over fitting and reduce the complexity of the model. It facilitates in the last decision-making process prediction. In summary, the Flatten operation enables to extract and leverage high-level features from images, enhancing the accuracy and efficiency.

D. Feature Extraction and Statistical Analysis

Feature extraction is very important in object recognition, and it is widely applied in various picture processing applications. For this, several characteristics can be utilized, including color, texture (which encompasses factors such as color distribution, brightness, and image smoothness), morphology, and edges, among others. However, processing the entire input data directly can be computationally intensive and prone to redundancy. To address this challenge, it is common practice to convert the input data into a condensed feature set or representations, which effectively captures the essential information. This transformation of input data into a concise set of some features is known as feature extraction. By extracting key features, the subsequent analysis and classification tasks can be done more efficiently and effectively.

The CNN has convolutional layers that consist of learnable filters that extract low-level features such as edges, corners, and textures, which are crucial for identifying signs of disease in a plant image.

Non-linear activation functions, such as ReLU, introduce non-linearity into the network, allowing for the learning of more complex and abstract representations. Pooling layers reduce the spatial dimensions of the feature maps, preserving relevant information while reducing computational complexity. Through these processes, the CNN progressively generates higher-level feature maps, capturing global structures and patterns essential for leaf disease prediction. By leveraging these extracted features, we can accurately classify and diagnose the disease, enabling timely intervention and prevention

E. Classification

The algorithm is a supervised learning technique that utilizes training data to categorize new observations into specific classes. By learning from the provided dataset or predefined classification criteria, the algorithm can accurately classify fresh observations into different categories or classes. These categories can be termed to as targets, labels, or divisions.In Fig 4 convolutional layers perform operations to extract meaningful feature from data that is given as input, while the max pooling layers down sample the spatial dimensions of the feature maps. The flatten layer reshapes the output into a one-dimensional vector, that are then used as input into the dense layers. The dense layers are fully connected and generate the final output. The network has a total of 184,202 trainable parameters, which are updated during the process of training to optimize the model's performanceIn the context of tomato leaf disease prediction, neural networks are often used to analyze plant images and identify signs of disease in plant leaves. The big number of trainable parameters suggests that complex architecture in the model is capable of capturing intricate patterns and features from the pictures to make accurate predictions regarding the presence and disease.The provided CNN (Conv Net) architecture in Fig 5 is designed for disease prediction in leaves. It begins with a data augmentation layer that introduces random transformations to diversify the training dataset. The subsequent convolutional layers perform feature extraction, utilizing different numbers of filters to capture varying levels of features. Max pooling layers are employed to down sample the feature maps, reducing their spatial dimensions while retaining important information. A global average pooling layer further reduce the quality of the features. The model concludes with a dense output layer responsible for classification, with 10 units representing the disease categories. The soft max activation function generates a probability distribution over the disease categories. With total of 10,490 trainable parameters, this architecture is ready for training and prediction tasks related to leaf classification in with respect to diseasese

F. Inception V3 Model

The provided InceptionV3 model architecture defines a deep learning model for image classification using the InceptionV3 architecture. It starts by loading the InceptionV3 model with pre-trained weights from the 'image net' dataset and freezing the weights of all layers. The model is then customized by adding additional layers for extracting features and classification. The result of the model is a probability distribution over the classes. By leveraging pre-trained weights and adding custom layers, the model can learn meaningful features from input images and classify them into different classes. Total of 26,220,042 trainable parameters, this architecture is ready for training and prediction tasks related to tomato leaf disease classification

IV. RESULTS AND DISCUSSIONS

In our study, we have conducted a comprehensive study of research papers that make use of Machine Learning for leaf disease identification. We have compared the findings from various published models and observed that CNNs demonstrate high accuracy in disease identification when trained on sufficient data. Our Findings and their accuracy are depicted in Table I as a result. Here from our findings, we are able to comprehend that high accuracy is achieved by implementing CNN (Conv Net) algorithm with the accuracy of 98.20% and we can also deduce that most published studies utilize convolutional neural networks for tomato plant disease identification

The result analysis holds significance in all forms of research. Therefore, in this particular study, the entire dataset that consists of approximately 10,000 images was segregated into two groups: 80% is for training purpose and other 20% is for testing purposes. With the survey result we conducted we chose some selected algorithms namely, AlexNet, CNN (Conv Net) algorithm and InceptionV3 algorithm to compare accuracy on the dataset same as previous that we got on Kaggle. Subsequently, the training dataset, comprising 80% of the data, was utilized to apply AlexNet algorithm, InceptionV3 algorithm and a CNN (Conv Net) algorithm.

The accuracy for classification is a performance standard measure used to evaluate the efficiency of the classifier. Training accuracy and testing accuracy are found out and finally, accuracy among three classifiers is shown below in Fig. 6.

A confusion matrix is a square matrix where the rows represent the actual labels of the images, and the columns represent the predicted labels of the images. This is confusion matrix that shows the quantitative numbers of true positive, true negative, false positive, and false negative predictions made by the models. The confusion matrix for best performing algorithm is depicted in Fig 7.

V. CONCLUSION

This study introduces a classification method aimed at identifying leaf diseases accurately. Multiple machine learning algorithms, namely Alexnet, InceptionV3, and a CNN (Conv Net) algorithm, were employed to classify the extracted features that are taken from the database leaf diseases images from tomato plant. CNN (Conv Net) algorithm demonstrated superior performance. The uncovering of this paper has practical implications, particularly in distinguishing between healthy and diseased tomato leaves

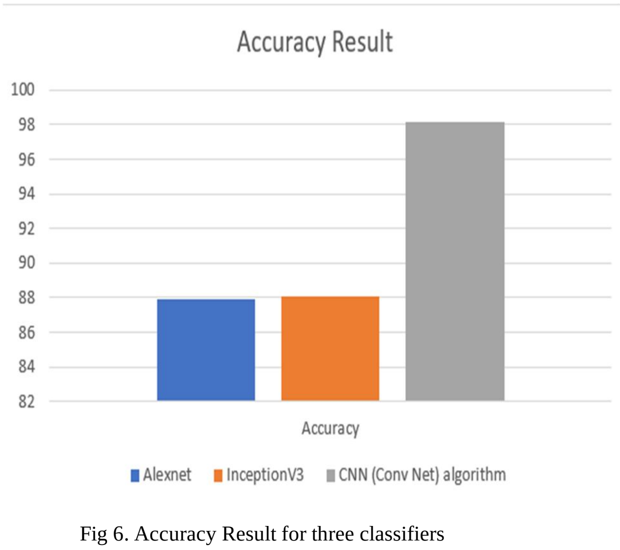

Fig 6. Accuracy Result for three classifiers

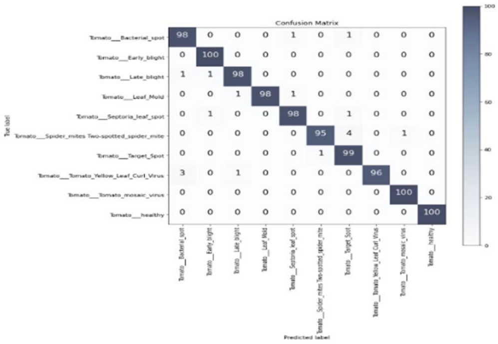

Fig 7. Confusion matrix comparing predicted and actual result obtained through model giving highest accuracy

REFERENCES

[1] Fuentes, Alvaro, et al. "A robust deep-learning-based detector for real time tomato plant diseases and pests recognition." Sensors 17.9 (2017)

[2] Durmuş, Halil, Ece Olcay Güneş, and Mürvet Kırcı. "Disease detection on the leaves of the tomato plants by using deep learning." 2017 6th International Conference on Agro-Geoinformatics. IEEE, 2017.

[3] Sardogan, Melike, Adem Tuncer, and Yunus Ozen. "Plant leaf disease detection and classification based on CNN with LVQ algorithm." 2018 3rd International Conference on Computer Science and Engineering (UBMK). IEEE, 2018.

[4] Arnal Barbedo, J. G., 2019 Plant disease identification from individual lesions and spots using deep learning. Biosystems Engineering, 180, pp. 96-107.

[5] Kumar, Akshay, and M. Vani. "Image Based Tomato Leaf Disease Detection." 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT). IEEE, 2019

[6] A. Elhassouny and F. Smarandache, "Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks," 2019 International Conference of Computer Science and Renewable Energies (ICCSRE), 2019, pp. 1-4, doi:

[7] D. Ireri, E. Belal, C. Okinda, N. Makange, and C. Ji, "A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing," Artificial Intelligence in Agriculture, vol. 2, pp. 28–37, Jun. 2019, doi: 10.1016/j.aiia.2019.06.001.

[8] Karthik, R., et al. "Attention embedded residual CNN for disease detection in tomato leaves." Applied Soft Computing 86 (2020): 105933.

[9] Ashok, Surampalli, et al. "Tomato Leaf Disease Detection Using Deep Learning Techniques." 2020 5th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2020.

[10] M. Agarwal, S. Kr. Gupta, and K. K. Biswas, "Development of Efficient CNN model for Tomato crop disease identification," Sustainable Computing: Informatics and Systems, vol. 28, p. 100407, Dec. 2020, doi: 10.1016/j.suscom.2020.100407.

[11] J. Lee, H. Nazki, J. Baek, Y. Hong, and M. Lee, "Artificial Intelligence Approach for Tomato Detection and Mass Estimation in Precision Agriculture," Sustainability, vol. 12, no. 21, p. 9138, Nov. 2021, doi: 10.3390/su12219138.

[12] J. Rong, G. Dai, and P. Wang, "A peduncle detection method of tomato for autonomous harvesting," Complex & Intelligent Systems, Sep. 2021, doi: 10.1007/s40747-021-00522-7.

[13] N. K. Trivedi, V. Gautam, A. Anand, H. M. Aljahdali, S. G. Villar, D. Anand, N. Goyal, and S. Kadry, "Early detection and classification of tomato leaf disease using high-performance deep neural network," Sensors, vol. 21, no. 23, p. 7987, 2022

[14] H. Kibriya, R. Rafique, W. Ahmad and S. M. Adnan, "Tomato Leaf Disease Detection Using Convolution Neural Network," 2022 International Bhurban Conference on Applied Sciences and Technologies (IBCAST), 2021, pp. 346-351, doi: 10.1109/IBCAST51254.2022.9393311.

[15] Ashqar, B.A.M., Abu-Nasser, B.S. and Abu-Naser, S.S., 2022. Plant Seedlings Classification Using Deep Learning. Available from: https://www.ijeais.org/ ijais

[16] L. Sherly Puspha Annabel, T. Annapoorani and P. Deepalakshmi, 2019, International Conference on Communication and Signal Processing

[17] Rishabh Mudgil, Nidhi Garg, Preeti Singh, Charu Madhu, 2022, IEEE World Conference on Applied Intelligence and Computing

[18] Hepzibah Elizabeth David, Hemalatha Gunasekaran, K. Ramalakshmi, 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)