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Exploring the Effectiveness of Machine Learning Algorithms for Tomato Leaf Disease Classification Using Multiple Image

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Abstract*- Tomato cultivation is critical to global food security; however, disease outbreaks can severely impact yield and quality. This study investigated the efficacy of different machine learning algorithms in categorizing tomato leaf diseases using diverse image sources. The algorithms examined were Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Random Forest (RF). Our results demonstrated that the CNN model surpassed the other two algorithms, attaining the best level of accuracy in categorizing tomato leaf illnesses. To improve the accuracy of categorization, we used a soft-voting classifier based on the results of various algorithms, creating a hybrid model. The soft voting classifier exhibited exceptional enhancement in precision and resilience, surpassing the performance of the separate models to a large degree, with 97.13 accuracy. These findings indicate that utilizing the advantages of several machine-learning algorithms can result in better performance in classifying plant diseases, presenting a promising avenue for future research in precision agriculture. This approach offers a promising solution for the accurate and efficient diagnosis of tomato crops, facilitating timely intervention and improving yield management.***Keywords: Tomato leaf, Disease, Machine Learning, ML Algorithm detection, Deep learning***

I. INTRODUCTION

India grows tomatoes as one of its essential agricultural products while they belong to the plant family Solanaceae. The annual tomato output in India now surpasses all countries apart from one and exceeds 18.7 million tons each year. The main tomato crops grown in India exist as heritage sites and roma varieties together with pear and beefsteak and cherry types. Different tomato diseases which trigger crop failure include anthracnose together with soil rot, canker viral species and bacterial strains in addition to leaf blights and spots. The early discovery of plant pathogens allows farmers to minimize crop damage because it is always more effective to prevent problems than to treat them. Plants encounter reduced crop production when pests and diseases damage them seriously or cause their complete death. Scarce current data exists about disease prevention methods and pest control strategies throughout different regions of India.

Different methods are used in sustainable agriculture to decrease post-harvest practices and enhance yield production. Complex calculations associated with disease detection methods such as PCR and mass spectrometry and gas chromatography and thermography and hyperspectral techniques and color recognition drive expenses to higher levels. The existing detection systems function through server integration and mobile technology using high-end CPUs and powerful processors and advanced cameras [1]. The detection capabilities of machine learning and deep learning technologies become more effective when employing fuzz logic neural networks and deep neural networks as the main detection methods. Disease detection methods for tomato leaves require identification of their distinctive characteristics which include color, shape and texture according to this study.

II. LITERATURE SURVEYS

The cultivation of Golden-quality tomatoes remains difficult because of biological leaf diseases. An inspection of leaf textures along with color alterations can help identify the leaf diseases that affect golden-quality tomatoes including early blight and late blight and septoria leaf spot and leaf mold and bacterial spot. The detection of diseases becomes possible through computer vision by means of both feature extraction and contextual description and database matching [2].

The acquisition of Tomato leaf images happens through handheld and UAV-mounted cameras that utilize GPS functionality for location tagging. RGB images first transition to grayscale then proceed to noise treatment and histogram normalization. The extraction process of features

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uses FAST in combination with SIFT and SURF and BRIEF together with ORB while RANSAC manages inconsistent features. The matching process of images depends on usage of similarity index and distance metrics along with correlation metrics for analysis.

The use of machine learning applications for classification tasks exists according to [3] and [4]. According to [5] vector machines produced results for disease detection. The study by integrated LSTM and CNN models to handle both spatiotemporal factors within their approach. Deep learning provides improved results over conventional image processing because it establishes systems which detect illnesses with precision and scalability[6][7].

The image pre-processing involved both resizing and contrast enhancement while changing colour space formats [8]. The K-means clustering method with GLCM conduct segmentation and feature extraction operations. The research utilized a multiclass SVM for classification functions. R. The transformation of main leaf colours produces LAB data. The k-means clustering method applied segmentation functions to process the data[9][10]. GLCM was used for feature extraction while SVM carried out the classification process. The research team used digital cameras to obtain images which underwent median filtering enhancement. K-mean clustering served as the main mechanism for Picture segmentation. The process began after image enhancement through K-mean clustering. An SVM served as the main method during classification stage. The affected areas needed identification through segmentation procedures [11][12]. The conversion from RGB to HSI is conducted through the combination of Otsu's detection with k-means clustering algorithm. After that the algorithm analyzed spots and borders for segmentation purposes. The pre-processing stage by [13][14] consisted of adjusting and normalizing the contrast levels. The process continued with bi-level thresholding followed by YCBCR application[15]. [16] utilize HMM and GLCM during their approach.

Image segmentation allowed us to take backgrounds off from the pictures[17]. Our classification system included KNN, ANN and SVM methods. Based on [18] KNN uses trained subject information to identify test sample group memberships from tested subjects distances. Our model worked to obtain image processing techniques for threshold and morphology. A multiclass SVM tool started working after completing the classification steps. The system split the images based on LAB colour measurement to produce visual markings from picture sections. Our system extracted features using the GLCM tool. [19] took plant photos with digital cameras to find and examine bacterial damage, sun damage, early tissue death, and fungi in rose plants, beans, lemons, and bananas. The threshold process converted the entire green background from color to black and white elements. The genetic algorithm performs the first stage by producing segmented images from the next step. Our team obtains details using processed pictures that are split through modifications to color co-occurrence. The minimum distance and support vector machine classification system helped to separate different items in our analysis. Studies show AI-based IT layout analysis systems achieve 97.6% accuracy on their evaluations while various companies check if AI technology can make this process better.

The research of Sunil [20]. analyzed disease control in precise agriculture through image-based evaluations and utilized SVMs together with CNNs and reinforcement learning algorithms to perform diagnostics. The evaluation included a comprehensive examination of the benefits and drawbacks followed by the issuance of operational suggestions. The analysis of Wang dataset demonstrated a logistic regression coefficient of -0.67 alongside an Area Under the Curve of 0.96 which supports proper early disease detection in sustainable agriculture systems.

[21] analyzed smart agricultural issues linked to environmental biohazards including climate change and population growth because of their impact on food security in their 2022 research study. The Egyptian government implements preventive measures to manage tomato diseases because tomatoes stand as an essential vegetable agricultural product. Deep learning analysis through ResNet50, InceptionV3, AlexNet and MobileNetV3 constitutes the core technological method for detecting diseases on tomato leaves.

The authors [22] employed CNNs in tomato leaf disease detection while advancing results through data augmentation along with transfer learning applications to improve crop production and classification accuracy. The database containing images of diseased tomato leaves underwent testing with CNN models to achieve enhanced results in disease recognition.

III. PLANT LEAF DISEASE DETECTION USING MACHINE LEARNING AND COMPUTER VISION

Modern technologies let society produce enough food to meet its needs. Modern society cannot reach both safe crop production and safe food requirements. Farmers currently face three major problems of plant health, decreasing pollinator numbers, and changing climate patterns. Your priority must be to invest into these basic areas first. Farmers can solve their difficulties by using technical tools and detection methods provided by modern technology. Recent technology shows how India exercises disease control to stop the spread of COVID-19 pandemic and future health emergencies. [23][24] Plants diseases return agricultural conditions to danger because they cause both dry soil phases and food failures. When disease affects commercial farmland it results in major money losses for farmers. The combination of computer vision and machine learning solutions proves protective against plant diseases according to [25][26] and [27].

IV. BIOLOGICAL CLASSIFICATION OF DISEASES AFFECTING TOMATO LEAVES

The growth of excellent tomato types faces significant difficulty from biological leaf diseases. To recognize tomato diseases you need to inspect not only leaf shape but also texture along with color and diverse other characteristics. Tomato diseases show their presence by distinctive patterns on the leaves[28][29]. Major diseases affecting tomatoes include three important infections: Early blight, late blight, Septoria leaf spot, leaf mould and bacterial spot. Some disease detection uses various computer vision methods that find and describe features from images while matching them to a feature database [2]. Researchers performed scientific tests on how machine learning tools identify different objects. To obtain the photographed tomatoes needed either handheld camera tools or camera equipment mounted on Unmanned Aerial Vehicles (UAVs). UAV cameras linked to GPS sensors help Users to mark leaf images with precise coordinates [5]. The images with RGB color data transformed into grayscale data. The team made all photos fit a regular 256 by 256 pixel format for their analysis. To get image features from digital photos you need to apply both noise removal and histogram equalization as conditions for image pre-processing steps. This step uses all available measurements of light quality and object dimensions.

V. KEY ISSUES AND CHALLENGES

While studying plant leaf diseases, researchers have identified major concerns and obstacles [3, 4]. Some main concerns are -

1. The quality level of leaf images used as Input layout should be highest possible.
2. Public dataset required.
3. Data contaminations create changes in leaf test specimen quantities.
4. Detecting diseases through segmentation methods requires extensive training along with testing of the utilized samples and specimens.
5. Detecting leaf diseases poses a challenge because of the difficulties involved in classification processes.

Where the proposed model overcomes those difficulties employing technologies from IP and ML to increase accuracy. ML and IP is suggested as a method for automatic leaf disease detection in this study.

VI. RESEARCH GAPS

There are several research gaps as to the efficacy for machine learning algorithms in disease classification of tomato leaves from several picture sources.

1) Although the title implies that several image sources (such as RGB, hyperspectral, and infrared pictures) would be utilized, it is not known how thoroughly these sources will be integrated into the categorization system. Investigations into the best approach to integration and the relative merits of each picture source, both individually and in combination, may yield fruitful results.
2) Plant health, sunlight, and background conditions can greatly affect tomato plant growth; therefore, it is important that tomato plants are able to withstand a wide range of situations. Research on how well machine learning algorithms perform in such diverse environments is essential for their practical use. One way to determine where the algorithm is lacking or could use some work is to test it in various environments with varying lighting, backdrops, and stages of plant growth.
3) Squaring the Gap between Socioeconomic Status and Disease Symptoms: Disease classification tasks are greatly complicated by factors such as class imbalance, in which some disease classes are overrepresented in the dataset, and the diversity in illness symptoms. Possible areas of research include methods to account for symptom fluctuations and to reduce the impact of class imbalance. To address class imbalance and unpredictability, this can include data augmentation, transfer learning, or ensemble approaches.
4) Applicability to Other Tomato Varieties and Disease Strains: Because different tomato varieties and disease strains have diverse leaf morphologies and symptoms, the efficiency of machine-learning methods may differ across these groups. Classification models must be tested for generalizability across different tomato varieties and disease strains before they can be used in agricultural settings. Gathering data from several tomato varieties and disease strains could be part of this process to assess algorithm performance in diverse scenarios.

VII. AIM AND OBJECTIVES

The following research goals can be developed based on the highlighted knowledge gaps.

1) Maximizing Classification Performance with Minimal Computational Complexity: Design and test algorithms to integrate various image sources (e.g., RGB, hyperspectral, infrared) into a single framework for disease detection in tomato leaves.
2) Approaches are needed to enhance the resistance of machine learning algorithms when dealing with environmental factor fluctuations during tomato leaf disease classification. such as illumination, backdrops, and plant health status. To address environmental unpredictability, it is necessary to create data preparation methods or adaptive learning methodologies.
3) The dataset contains information about disease symptoms; however, there is a significant class imbalance. To mitigate this, we need creative techniques to manage this imbalance and variability. To better represent underrepresented groups and account for symptom variability, this involves exploring strategies,

including instance selection, synthetic data generation, and class-weighted loss functions.

4) When gathering and annotating datasets, ensure that they cover a wide range of genetic backgrounds and symptoms. Then, we test how well the machine learning models work with various tomato varieties and disease strains. Determine which factors affect generalizability and how to make the model more transferable by evaluating its performance with cross-validation and transfer learning.

VIII. PROBLEM FORMULATION

The researchers conducted this study to evaluate machine-learning model performance in disease classification of tomato leaves by utilizing multiple photograph types including RGB, hyperspectral, and infrared. The research focuses on resolving essential problems related to uniting diverse imaging systems while maintaining cross-environment functionality along with disease syndrome harmonization and extending testing capabilities to different tomato strains and diseases and enhancing the clarity and logic behind classification choices.

IX. RESEARCH METHODOLOGY

With the tomato leaf illness dataset consisting of 11,000 images containing 10 different pathogen-affected tomato leaves the research team conducted their analysis. Each group of seven diseases in the dataset had 1,100 sample images within its category. These categories contained tomato mosaic virus, target spot, bacterial spot as well as late blight, early blight, spider mites (two-spotted spider mite) and healthy tomato along with septoria leaf spot. Users can find the available dataset on Kaggle. The different characteristics of various diseases in tomato leaves are shown in Figure 1. Kaggle link provides access to the data collection which became available on August 20, 2024.

Fig 1. Proposed Sample of tomato leaf dataset Image Classification (only a few)

TABLE 1: TOMATO LEAF MEDICAL CONDITION AND ITS FEATURES CLASSIFICATIONS LAYOUT

Class	Number of samples	Description
Mosaic virus	1100	Mosaic virus is a plant disease characterized by mosaic-like patterns on leaves, caused by various viral strains. It spreads through infected seeds, plant debris, or insects, leading to stunted growth and reduced crop yield.
Target spot	1100	Target spot is a fungal infection that damages tomato plant leaves by generating circular spots which display ring patterns. The disease causes leaves to fall off and decreases fruit quality unless fast remedial steps with fungicidal techniques and sanitary practices are implemented.
Bacterial spot	1100	The disease known as bacterial spot affects tomato leaves through its development of dark water-soaked spots which later turn black or brown. The disease produces severe leaf loss resulting in yield reduction unless farmers use copper-based fungicides along with crop rotation practices.
Yellow leaf curl virus	1100	Tomato plants face devastating effects from yellow leaf curl virus that produces yellowed leaves accompanied by leaf upward curling. Whiteflies transmit this virus causing detrimental yield losses when there is no implementation of pest management combined with resistant plant selections.
Late blight	1100	Late blight damages tomato plants through fungal infection leading to quick spread of dark water-soaked discolorations on leaves that results in plant wilting. The combination of improper fungicide use and unsensitised plant maintenance will cause complete crop destruction in a brief period due to the disease.
Leaf mold	1100	Leaf mold presents as a fungal condition of tomato leaves through combined symptoms of yellowish-green to brownish patches on top while fuzzy white to gray mold appears on the underside. The fungus favored by hot humid environments can be controlled through suitable ventilation methods and fungicide treatments and by eliminating damaged plant residues.

Classifiers

Three machine learning models support vector machines random forests and convolutional neural networks serve as the investigative methods within this research.

The support vector machine algorithm builds a hyperplane for classification through supervised machine learning by establishing maximal class separation. The research adopted a SVM model which employed 'rbf' Kernel method. The RBF kernel function determines the similarity of spatial relationship between the two points X_1 and X_2. This kernel follows the following mathematical expression.

$$K(X1, X2) = exp\frac{||X1 - X2||}{2\sigma^2}$$

Random Forest

The supervised learning Random Forest classifier works as an algorithm to produce predictions. The algorithm bases its work on a dataset to create decision trees which produce predictions that voting selects according to their accuracy levels.

Convolutional Neural Network

Neural networks known as convolutional neural networks discover automatic optimized features from data using filters (or kernels) through their automated processes. The implementation of regularized weights across reduced network connections was a solution to rectify both gradient vanishing and exploding gradients problems which occurred during backpropagation in traditional networks.

The Soft Voting Classifier acts as a hybrid model to merge multiple machine-learning classifier results through a voting mechanism. The machine-learning model involves a soft voting classifier that unites multiple individual predictions through analysis of each class label probability.

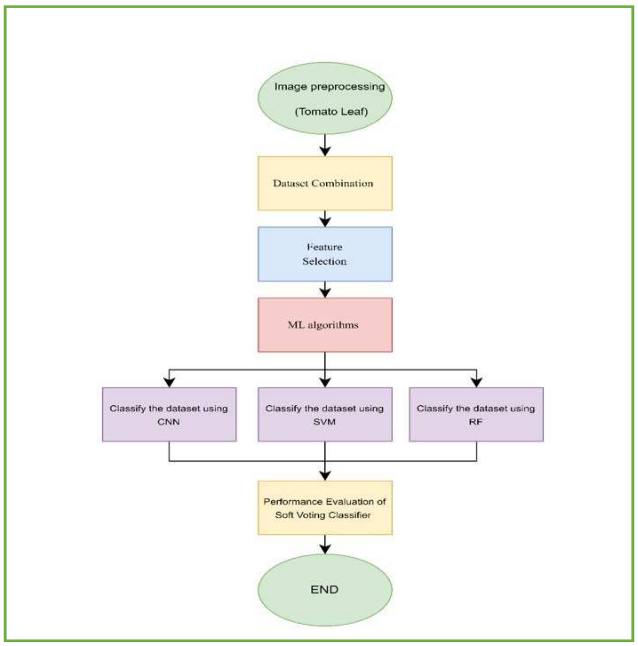

Fig 2. Proposed Methodological Layout

Effective classification of figure 2 tomato leaf photos needs an assemblage of multiple methods for complete success. Before processing leaf images the optimized picture techniques make the pictures better and clearer. A system was established using different tomato leaf samples to show all features between plants.

The next step involves selecting techniques that extract and filter visual elements for better classification analysis. Our data features are entered into CNN, SVM, and RF classification model systems that boost sorting accuracy plus let the system learn from experience continually.

SVMs help us classify items well despite dealing with large sets of data making them crucial for better processing. The calculated output stem from the class holding the highest probability value.

Methodology

Pre-processing follows data collection which produces both diverse images and separate training datasets of 10,000 and validation datasets of 1,000 (Figure 2). The system utilizes reinforcement learning for decision optimization and features extraction through CNNs and contains additional ML model exploration including SVMs. Quantum hardware serves as an acceleration solution while feedback processes occur in real-time and continuous learning becomes incorporated through this system. Evaluation uses standard metrics along with input variations analysis to create interpretable outputs that reach conclusions and offer deployment guidelines for agriculture.

Performance metrics help determine if classification works properly but sensitivity testing shows feature impact on the output result. The final solution delivers reliable tomato leaf classification with room for future progress and improvement.

Data Mining research makes regular use of Accuracy, F-measure, precision, and recall as performance evaluation measures. This research investigates the performance evaluation criteria.

According to (1) the formula shows accuracy as the relationship between correctly classified cases to all instances present in the dataset. It can be stated as follows:

$$Accuracy = \frac{(Trpo)+(TrNe)}{(TrPo)+(FlPo)+(TrNe)+(FlNe)} \quad (1)$$

Precision within a modelling system describes the relationship between actual positive predictions and all presented positive manifestations made by the model.

$$\text{Precision} = \frac{(TrPo)}{(TrPo)+(FlPo)} \quad (2)$$

Using geometric mean measures the ratio between successful positive event predictions and all positive events in the sample. The true positive rate sometimes refers to this measure.

$$\text{Recall} = \frac{(TrPo)}{(TrPo)+(FlNo)} \quad (3)$$

The F1 score shows how effective precision and recall work together in a single numeric result. In this procedure we determine the harmonic average of recall and precision values. Measuring F1 Score helps find the right balance between excellent detection accuracy and thorough detection scope. This method applies direct impact when one or both parts generate severe negative results.

X. RESULT AND IMPLEMENTATION LAYOUT

This study used a dataset to identify different diseases found on tomato leaves. The database split into 80% training material and 20% test material for analysis.

This research explores the details of the dataset, training data, and testing data. A figure 3 shows the effectiveness of SVM classification when using the 'rbf' Kernel. The SVM showed poor results during assessment with a linear inner-product compared to its performance using the RBF function.

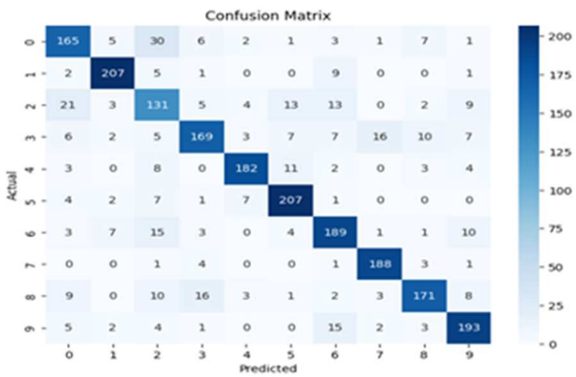

Fig 3. Confusion matrix of SVM

Figure 4 depicts the confusion matrix of Random Forest classifier. the results were not as good as SVM kernel.

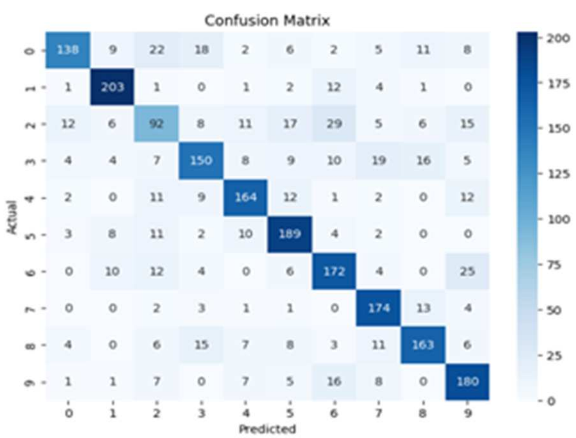

Fig 4. Confusion matrix of Random Forest

The CNN classifier results display in Figure 5. The CNN results surpassed both other models since CNN delivered better results than its competitors. Our tests focus on displaying all CNN model outcomes. Figure 6 unveils how properly the CNN-based machine learning model performs during multiple training phases before validation and training loss points. When the model found training patterns the losses from both training and validation decreased steadily at first.

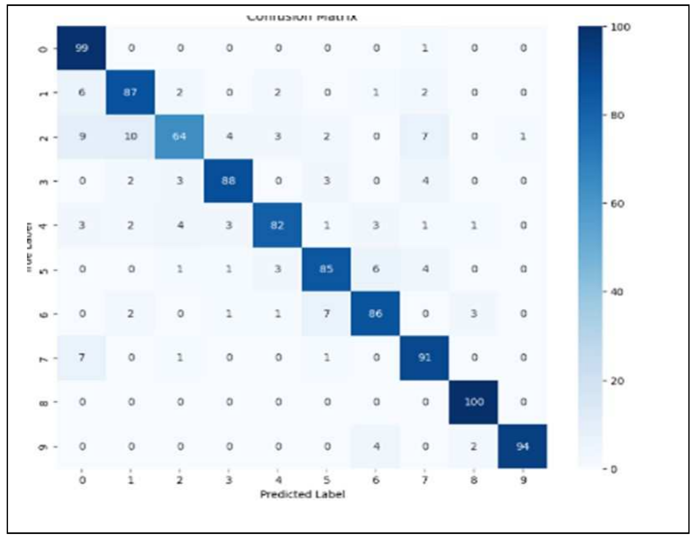

Fig 5. Confusion matrix of CNN Classifier

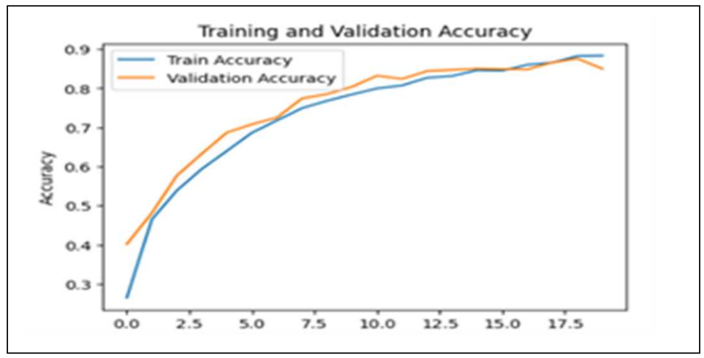

Fig 6. Training and Validation Accuracy

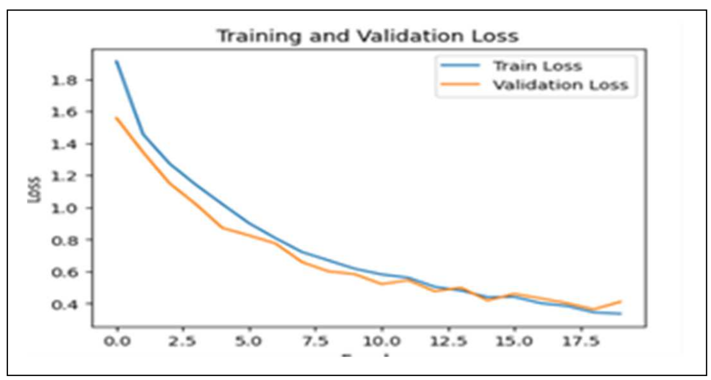

Fig 7. Training and Validation Loss

During training the validation loss keeps decreasing while the training loss faces a block and increases slightly past epoch 10. The model begins to detect too many false patterns during training which makes it have difficulties recognizing relevant patterns in new data. To secure better generalization our model we need to combine methods like early halting and regularization. The model needs more evaluation to identify why validation loss begins to rise.

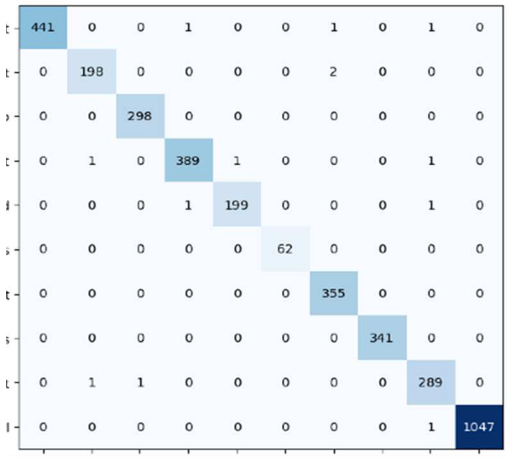

Fig. 8 Confusion Matrix of Soft voting classifier

A Soft Voting Classifier took results from three machine learning algorithms before creating more precise prediction results. By using this method the system successfully identified tomato illnesses at 97.13% accuracy with precise results.

This methodology comprises two steps. First the model learned about the untested dataset before using 20 percent of the remaining data for testing. The model received testing sets for evaluation that it learned from without adjusting parameter settings.

This test measures machine learning algorithm effectiveness to understand system weaknesses through complete assessment. The processed dataset received entry from each individual input after processing. The data for training filled 80 percent of the complete dataset. The information is easy to understand and direct.

Scientists studied both healthy and diseased tomato classes at different processing depths with multiple batch quantities. The research used data from ten classes to produce its results. Using four classifiers. Their experiment achieved successful results for both the training and evaluation data sets. The test results needed longer training time to stabilize as batch size values rose. An advanced soft computer classifier proved its best capabilities by recognizing 97.13% of items. Training and validation sets received an 80-20 partition with 40 items in each batch. According to the data the batch size made little difference to how well the model worked. Boosting batch size led to later identification of stable outcomes in the test process.

The results reveal that the classifiers vary in their resolution on different datasets owing to the differences in their functions. Table 2 presents the classification results of this study.

TABLE 2: MODEL'S PERFORMANCES BASED ON DIFFERENT PARAMETERS

Classifier	class	Precision	recall	f-1 score	Support	Accuracy
Support Vector machine	0	0.76	0.75	0.75	221	82.0
	1	0.91	0.92	0.91	225	
	2	0.61	0.65	0.63	201	
	3	0.82	0.73	0.77	232	
	4	0.91	0.85	0.88	213	
	5	0.85	0.90	0.88	229	
	6	0.78	0.81	0.88	233	
	7	0.89	0.95	0.92	198	
	8	0.85	0.77	0.81	223	
	9	0.82	0.86	0.84	225	
Random Forest	0	0.84	0.90	0.87	225	74.0
	1	0.54	0.46	0.49	201	
	2	0.72	0.65	0.38	232	
	3	0.78	0.77	0.77	213	
	4	0.74	0.83	0.78	229	
	5	0.69	0.74	0.73	233	
	6	0.74	0.88	0.81	198	
	7	0.78	0.73	0.75	219	
	8	0.78	0.73	0.75	223	
	9	0.71	0.80	0.75	225	
Convolutional Neural Network	0	0.88	0.87	0.88	200	95.0
	1	0.73	0.80	0.76	200	
	2	1.00	0.80	0.89	222	
	3	0.83	0.98	0.88	200	
	4	0.89	0.80	0.94	218	
	5	0.76	0.65	0.70	201	
	6	0.54	0.75	0.63	200	
	7	0.79	0.75	0.77	232	
	8	0.85	0.85	0.85	200	
	9	0.89	0.84	0.90	222	
Soft Computing Classifier	0	0.97	0.95	0.97	242	97.13
	1	0.96	0.97	0.98	234	
	2	1.00	0.98	1.00	240	
	3	0.94	0.93	0.94	222	
	4	0.95	0.95	0.95	218	
	5	0.96	0.97	0.96	222	
	6	0.93	0.97	0.92	242	
	7	0.97	0.97	0.97	232	
	8	0.97	0.97	0.96	202	
	9	0.94	0.95	0.94	224	

XI. CONCLUSION

Studying machine learning systems shows they can effectively distinguish tomato leaf diseases through precision, recall exploration plus training and validation loss. The model learns to make predictions best during an initial phase but might start to over fit after this point based on validation loss data in the graph. The measurement demonstrates whether the developed model clearly differentiates between healthy and damaged tomato leaves before recommending proper treatments. This work uses evaluation criteria to show exactly how well machine learning systems identify tomato leaf diseases. Better farming techniques will now be possible for healthier crops through improved management practices.

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