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EFFICIENT PREPROCESSING TECHNIQUES FOR ACCURATE AND ROBUST FEATURE EXTRACTION IN DEEP LEARNING-BASED TOMATO LEAF DISEASE DETECTION: A COMPREHENSIVE REVIEW

Mr B L JayaKumar
Research Scholar, Presidency University,Bangalore

Dr. Manjula H M
Associate Professor Department of Computer Science and Engineering Presidency University,Bangalore

Abstract—Early and accurate detection of tomato leaf diseases is essential for minimizing crop losses and improving agricultural productivity. Deep learning models such as Convolutional Neural Networks (CNNs), Region-Based CNNs (R-CNNs), and other advanced classifiers have demonstrated strong potential; however, their performance greatly depends on the quality of preprocessing and the robustness of the extracted features. This comprehensive review examines state- of-the-art preprocessing techniques that enhance image quality, improve feature representation, and strengthen the reliability of deep learning-based tomato leaf disease detection systems. Key methods—including image scaling, color space transformations, noise reduction, contrast enhancement, segmentation techniques such as thresholding and flood filling, as well as feature extraction approaches like gradient- based descriptors and moment-based features—are critically analyzed
Keywords—Fuzzy Support Vector Machine (SVM); Convolution Neural Network (CNN); Region-based Convolution Neural Network (R-CNN); color thresholding; flood filling

I. INTRODUCTION

Tomatoes are a major commercial crop grown all over the world. It is sensitive to various illnesses, which reduces tomato quality and yield while also causing significant economic losses. Tomato grey leaf spot is a common disease that damages and kills the leaves of tomatoes, preventing them from growing and producing fruit. The infection that produces grey leaf spots on tomatoes is brutal to remove. Contact, invasion, latency, and onset are the four phases of infection for the pathogen that causes tomato grey leaf spot. As a result, early preventative and control methods are suitable before a large-scale pandemic. Early disease detection can also aid in reducing pesticide usage and pollution, as well as the quality, safety, and health of tomatoes. Traditional disease detection systems cannot meet large-scale planting demands due to low diagnostic efficiency and fast disease transmission, and plants typically miss the appropriate management time [1, 2].

Manually detecting leaf disease with the naked eye needs a team of professionals and ongoing monitoring. When the farm is large, it is costly. As a result, image processing techniques may be used to automatically detect illnesses in leaves, saving time, money, and effort as compared to traditional methods. The early detection of illnesses in leaves improves crop productivity. Disease-affected leaves may be found at an early

stage using image processing techniques like as segmentation, identification, and classification,

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and crop yield and quality can be improved. Many farmers lack the resources or understanding on how to contact specialists, which makes it more costly, time-consuming, and inaccurate. In this case, the suggested approach proved to be more advantageous in terms of crop observation. The technique is more accessible and less costly when plant illness is detected using leaf symptoms. It takes less time, effort, and precision to use an automated detection technique. Manually detecting leaf disease with the naked eye needs a team of professionals and ongoing monitoring. When the farm is large, it is costly.

As a result, image processing techniques may be used to automatically detect illnesses in leaves, saving time, money, and effort as compared to traditional methods. The early detection of illnesses in leaves improves crop productivity. Disease-affected leaves may be found at an early stage using image processing techniques like as segmentation, identification, and classification, and crop yield and quality can be improved. Many farmers lack the resources or understanding on how to contact specialists, which makes it more costly, time-consuming, and inaccurate. In this case, the suggested approach proved to be more advantageous in terms of crop observation. The technique is more accessible and less costly when plant illness is detected using leaf symptoms. It takes less time, effort, and precision to use an automated detection technique.

Image processing technology can quickly and accurately diagnose illnesses based on their features. Disease prevention approaches may be applied fast, and efforts to avoid additional illnesses can be performed using this strategy. People used to identify tomato ailments based on their own experiences, but the ability to discern between various diseases is limited, and the process is time-consuming. Machine learning and image processing technologies are fast expanding and more widely employed in various industries, including agriculture. The following are two key contributions of this research: R-CNN framework for classifying leaf diseases ii) comparison of different classifiers. The remaining sections of this work are organized as follows: Section 2 did a background survey. Section 3 is about methodology. In Section 4, we give experimental data and analyze it by comparing the best classifiers that may be employed based on the findings of our previous study. Section 5 summarizes the proposed work of this paper.

II. LITERATURE SURVEY

Traditional plant disease detection approaches based on computer vision technologies are commonly utilized to extract the texture, shape, color, and other features of disease spots. This method has a low identification efficiency because it relies on an extensive expert understanding of agricultural illnesses. Many academics have conducted significant research based on deep learning technology to increase the accuracy of plant disease detection in recent years, thanks to the fast growth of artificial intelligence technology [8]. The majority of existing techniques to plant disease analysis are based on disease classification [12].

Mohanty et al. [3] utilized GoogleNet and AlexNet to classify 54,306 plant leaf pictures as healthy or sick in the Plant Village dataset, revealing that GoogleNet had a slightly more significant average classification impact than AlexNet. The trained deep convolutional neural network model has a 99.35 percent accuracy on the test set. Building a deep learning model on a growing and publicly available photo dataset is a simple way to employ clever mobile phones to diagnosis plant diseases in horticulture crops.

Picon et al. [4] employed a deep residual neural network- based upgraded algorithm to identify

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many plant illnesses in real-world acquisition conditions. For early illness identification, several improvements have been recommended. According to the data, all of the illnesses evaluated had an AuC score of higher than 0.80.

Selvaraj et al. [5, 9] utilized the transfer learning approach to retraining three CNN architectures. Deep transfer learning was utilized to build networks using pre-trained sickness detection models to provide accurate predictions.

Deep learning was proposed by Fuentes et al. [6, 7] for identifying diseases and pests in tomato plant photos acquired at varying camera resolutions. Deep learning meta- architectures, as well as multiple CNN object detectors, were utilized. Data expansion and local and global class annotation were utilized to boost training accuracy and decrease false positives. A large-scale tomato disease dataset was used for end-to-end training and testing. The system correctly detected nine different pests and diseases from the complicated scenarios.

III. METHODOLOGY

Our primary objective is to develop a model to categorize input plant leaf pictures as healthy or unhealthy. The disease kind is also determined if a disease is detected on a plant leaf. Our study compares the R-CNN Classifier to previously established tomato leaf disease detection utilizing fuzzy SVM

[15] and CNN [16] Classifiers to detect and categorize tomato leaves suffering from common illnesses. Fig. 1 shows the architecture of the R-CNN-based plant disease detection system. The proposed technique includes image capturing, pre- processing, segmentation, feature extraction, classification, and performance assessment.

A. Dataset Description

The dataset utilized for this investigation has seven primary classifications. Six leaves classes represent unhealthy, while one represents the healthy leaf class. Each class has 105 examples for a total of 735 leaf images. A classification strategy is required to categorize input photos into one of the classes specified in Fig. 2 for a given image of an apple leaf.

B. Image Pre-processing

The visual noise of the tomato leaf is made up of dewdrops, dust, and insect feces on the plants. The input RGB image is transformed to a grayscale image for accurate results to remedy these concerns. The image size in this circumstance is relatively large, needing image resize. The image size is reduced to 256 * 256 pixels.

C. Image Segmentation

Plant disease detection and categorization rely heavily on image segmentation. The image is simply divided into various things or sections. It analyses visual data to extract information that may be used for further processing. Our prior work [15] is used to accomplish color thresholding and flood filling segmentations.

D. Classification using R-CNN

Rectangular regions are combined with convolutional neural network characteristics in R-CNN (Regions with Convolutional Neural Networks). The R-CNN algorithm employs a two-stage detection procedure. The first stage identifies a set of picture areas that includes a diseased part. In the second stage, each region's object is categorized.

1) R-CNN procedure: The following three approaches are employed to build an R-CNN based algorithm, as shown in Fig. 3.

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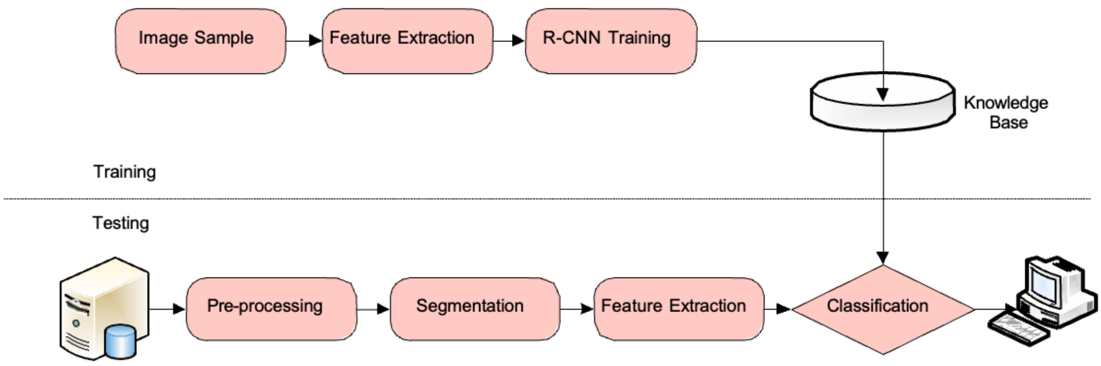
a) To find regions in a photograph that could contain a diseased part. Region suggestions are the names given to these locations.
b) Extract CNN characteristics from the region suggestions.
c) To categorize the objects, use the characteristics that were retrieved.

The R-CNN generates region recommendations using a mechanism similar to Edge Boxes [10]. The proposed elements have been chopped and scaled out of the image. CNN then classifies the clipped and resized regions. Finally, a support vector machine (SVM) trained on CNN features refine the region proposal bounding boxes. A visual illustration of the problem is shown in Fig. 3.

A pre-trained convolution neural network is used to build an R-CNN detector, also known as transfer learning (CNN).

As a starting point for learning a new task, we will use a pre-trained image classification network that has already learned to extract robust and informative features from raw photographs. A portion of the ImageNet database [10], which is used in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [11], is used in the great majority of pre- trained networks. These networks have been trained on over a million photographs and can categorize a large number of them. Transfer learning with a pre-trained network is typically much faster and easier than training a network from the ground up.



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Output

Fig. 1. Architecture of R-CNN-based Plant Leaf Disease Detection.

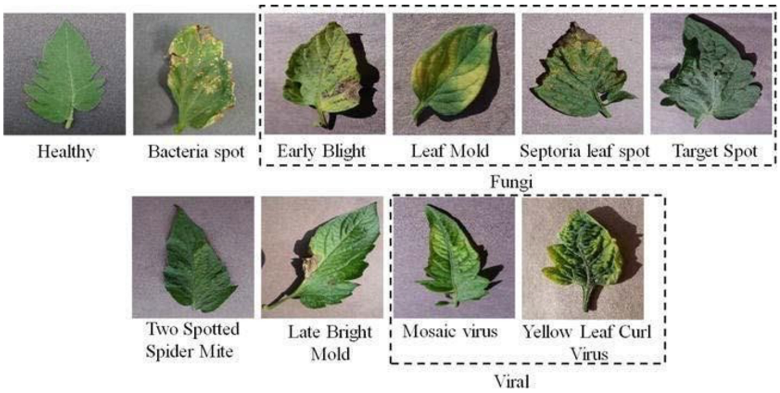
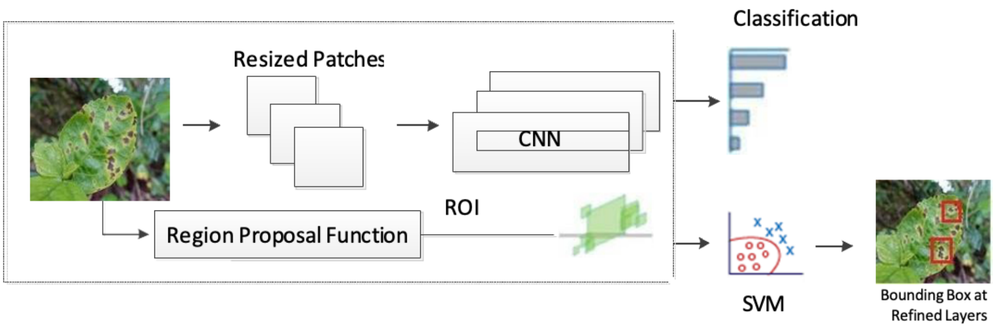


Fig. 2. Tomato Leaf Images with its Diseases.



Bounding Box at Refined Layers

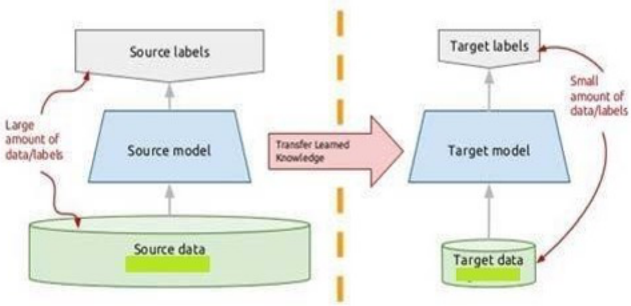


Fig. 3. Process of R-CNN Model.

2) Transfer learning methodology: The transfer learning method is employed a pre-built and pre-trained model rather than developing and training a CNN from scratch [13]. Transfer learning is a method based on transferring a model that has been trained on an extensive dataset to a smaller dataset. Early convolutional network layers are retained for object recognition and train the final few levels to generate predictions. The theory is that the convolutional layers extract broad, low-level properties from numerous pictures, such as edges, patterns, and gradients. On the other hand, the last layers identify individual characteristics inside a picture.
Fig. 4 depicts the principle of transfer learning [14]. Fig. 4. Concept of Transfer Learning.

A general framework for object recognition transfer learning is as follows:

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a) Insert a CNN model trained on an extensive dataset and is ready to use.
b) Freeze the parameters of the model's bottom convolutional layers (weights).
c) Add a custom classifier with many layers of trainable parameters to the model.
d) The task's training data should be used to train layers of classifiers.
e) Fine-tune hyperparameters and unfreeze more layers as needed.

This strategy has been proven to be effective in several sectors. It is a terrific tool to have in our arsenal, and it is generally the first thing we do when confronted with a new image recognition challenge.

3) Transfer Learning Characteristics:

a) It requires transferring information from one source task to the target task to learn and grow.
b) DNN trained on raw pictures has been observed to demonstrate an unusual occurrence in which the network's initial layer appears to gain Gabor filter-like properties.
c) The first layer's characteristics were found in a variety of datasets.
d) The initial layers' general characteristics disregard the picture dataset, task, and loss function.
e) The filters learned by specific ResNet layers can be reused by other ResNet layers if they learn the same feature. In convents, this practice is called extremely successful transfer learning.
f) While overcoming data shortage, transfer learning saves time and money in training.

4) R-CNN model design: To generate R-CNN models based on a previously trained CNN for image classification. The R-CNN model is built on the foundation of a pre-trained network. The last three categorization levels are eliminated, and new layers customized to the item types wish to detect are added in their place.

As shown in Fig. 5, the final three layers in this network are fc1000, fc1000 softmax, and ClassificationLayer fc1000; the last three levels in this network are fc1000, fc1000 softmax, and ClassificationLayer fc1000. Fig. 6 depicts the removal of the final three layers.

As indicated in Fig. 7, add the new categorization layers to the network. The layers are put up to categorize the number of items that the network should detect.

5) Convolution neural layers of RCNN model: The input layer, the initial layer of the R-CNN architecture, delivers raw data to the network. The 32*32*3 raw image was recorded. The properties are extracted via the convolution layer, the transformation layer. As a result, this layer's inputs were leaf pictures. The R-CNN model's first convolution layer consists of 32 different 3*3 filters, each having one stride and one

padding. After the convolution layers, the rectified linear unit layer (ReLU) is the most often utilized rectifier unit for neuron outputs. Pooling, commonly employed after the ReLu layer, decreases the subsequent convolution layer's input size (width and height). Fig. 8 depicts the entire structure.

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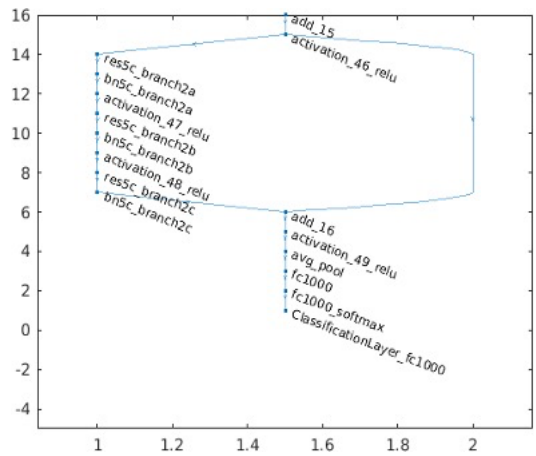

Fig. 5. Layers of ResNet-50 Pre-trained Network.

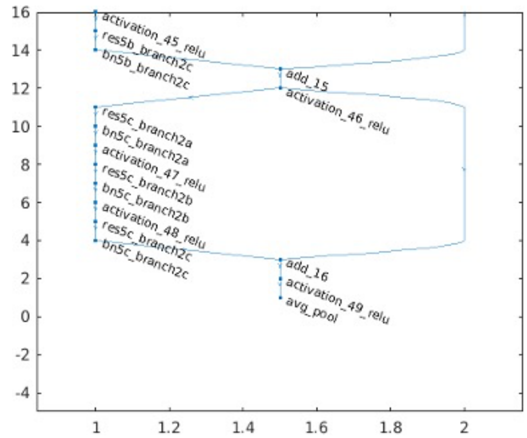

Fig. 6. Layers of ResNet-50 Network by removing Three Layers.

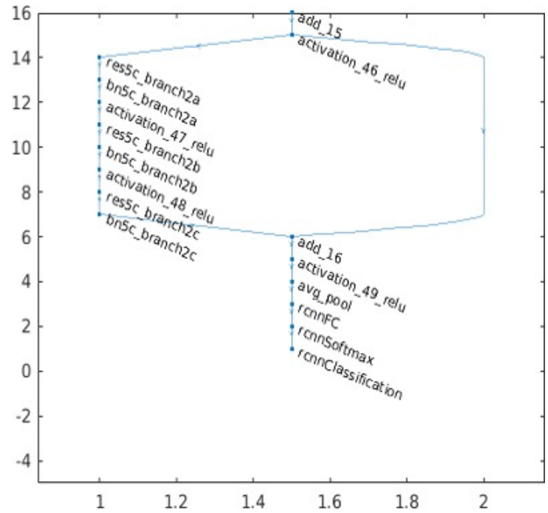

Fig. 7. Layers of ResNet-50 Network after addition of New Layers.

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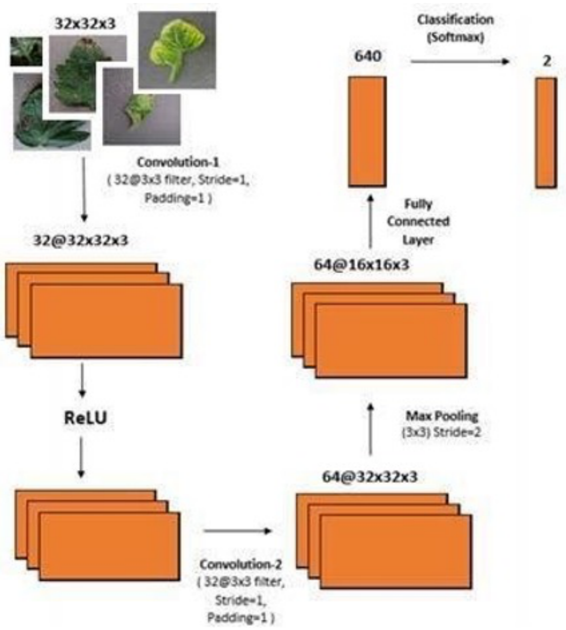

Fig. 8. Architecture of CNN Inside R-CNN.

The sub-maximum area's value was forwarded to the max- pooling layer. The scale value must be carefully controlled to avoid the attribute size reducing too quickly, the image attributes becoming rough, and the attributes getting lost in the max-pooling layer. There are layers for convolution, ReLU, and max-pooling before the finally linked layer. A 64-node fully connected layer was employed in the R-CNN. As a result, this layer is linked to the prior levels' core constituents. This layer is followed by the classification layer, which performs classification. A softmax classifier is a multi-class classifier based on an extension of the logistic function. The output map is connected to the Softmax function, the final layer of the proposed architecture, through the final convolution layer. It establishes the likelihood of each class.

IV. EXPERIMENTAL RESULT AND ANALYSIS

This section evaluates the performance of several classification techniques such as Fuzzy SVM, CNN, and R- CNN and shows that the Fuzzy SVM classification methodology surpasses the others. The datasets for tomato leaf disease are split into two categories: training data (70%) and testing data (30%). The Tomato Plant Disease dataset contains 735 pictures and seven classes named Bacterial Spot, Mosaic Virus, Yellow Leaf Cur Virus, Early Blight, Late Blight, Leaf Mold, and Healthy.

The implementation of these classifiers takes place in MATLAB 2019B. The input images as illustrated in Fig. 9, are pre-processed in this experiment to decrease noise, and then segmentation is performed using Color-thresholding and flood filling. The contaminated section of the leaf is then removed, and the GLTP and Zernike moments of that infected area are determined. Then, Classifiers are employed to determine the illness name.

The confusion matrix is a metric for evaluating the performance of a machine learning classification task with two or more classes as output. There are four distinct combinations of projected and actual values in this table. It's great for assessing things like recall, precision, specificity, accuracy, and, most crucially, AUC-ROC curves. The confusion matrix of R-CNN is shown in Fig. 10.

A Receiver Operator Characteristic (ROC) curve is a graphical representation of a classifier's diagnostic capabilities. The ROC curve depicts the sensitivity vs. specificity trade-off. Classifiers with curves that are closer to the top-left corner perform better. The ROC curve that was developed for R-CNN is shown in Fig. 11.

Fig. 9. RCNN-Trained ResNet 50 Sample Results.

R-CNN Confusion Matrix

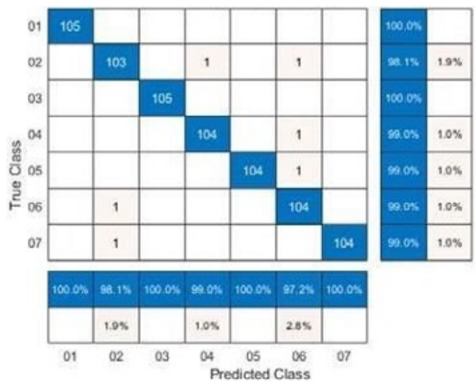

Fig. 10. Confusion Matrix of R-CNN Classifier.

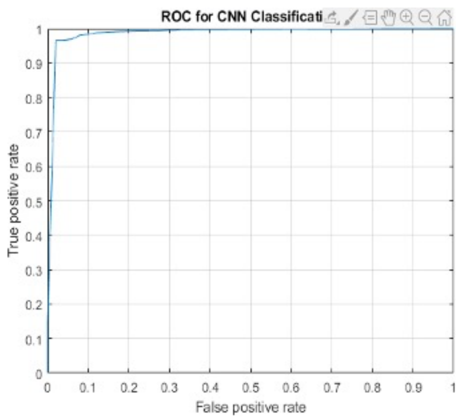

Fig. 11. ROC Curves for R-CNN Classifier.

The confusion matrix of CNN, and fuzzy-SVM, respectively, are shown in Fig. 12, and 13.
Fig. 14 depicts the classification accuracy for all the 3 classifiers as a comparison analysis. The leaves are classified as healthy or unhealthy and the type of condition if they are diseased.

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Precession, recall, and accuracy are the other performance indicators shown in Fig. 15 for all of the classification algorithms for tomato leaf disease datasets.

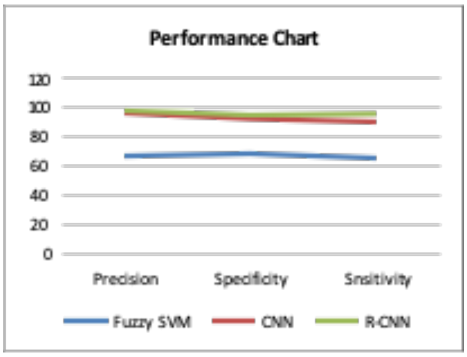

Fig. 12. Confusion Matrix of CNN Classifier.

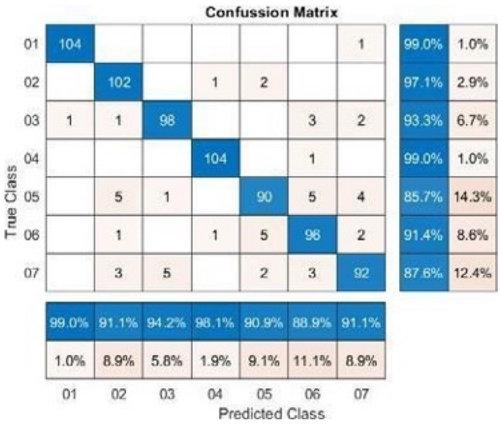

Fig. 13. Confusion Matrix of Fuzzy SVM Classifier.

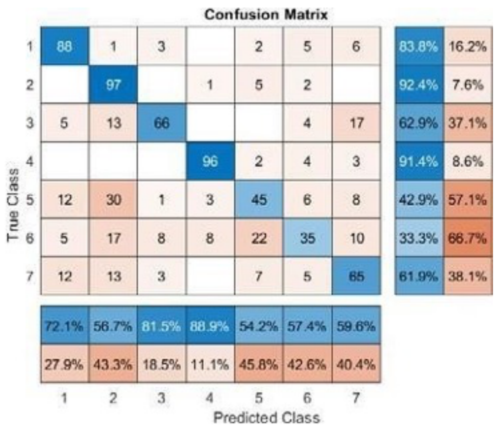

Fig. 14. Comparison between Classification Techniques.

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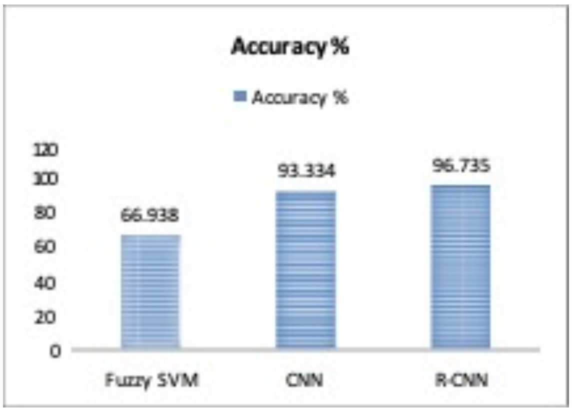

Fig. 15. Precision, Specificity and Sensitivity of Classifiers.

Previously developed models are used for performance comparison using the confusion matrix. The following is a quick summary of these models: The confusion matrix for R- CNN findings for 735 input leaf samples is shown in Fig. 10.

A healthy and unwell people database is produced in a Fuzzy SVM-based Classifier [15]. There are six distinct illnesses and 735 photos in the classes in the input database. Color thresholding and flood filling are the two segmentation techniques used. For greater accuracy, the output of both algorithms is integrated using ROI (region of interest). The diseased section of the leaf's characteristics was extracted using the segmented picture. The Color Covariance Vector (CCV) and Gradient Direction Pattern (GDP) algorithms are employed. This phase extracts a total of 56 color features and 256 gradient characteristics. With 420 photos in four classes and a parentage accuracy of 97.142, this Fuzzy SVM algorithm provides the best results. However, increasing the number of photos from 420 to 735 reduces performance to 66.938 percent. A CNN-based classifier is employed to increase performance.

The CNN-based Classifier [16] includes 735 healthy and ill plant leaves. Among the seven forms of tomato leaf diseases in the database are Bacterial Spot, Mosaic Virus, Yellow Leaf Cur Virus, Early Blight, Late Blight, and Leaf Mold. The images were all shot in a lab environment. The images of leaves were divided into two categories: training and testing. Leaf images are separated into two groups to test performance: 70–30 (70 percent of the photos are for training, and 30 percent are for testing). The segmented section is used to retrieve the unhealthy portion of the leaf.

V. CONCLUSION

This comprehensive review highlights the critical role of efficient preprocessing techniques in enhancing the accuracy, robustness, and generalization capabilities of deep learning models for tomato leaf disease detection. While CNNs, R-CNNs, and other modern architectures have shown impressive classification performance, their effectiveness largely depends on the quality of input images and the discriminative strength of extracted features. Techniques such as image resizing, color normalization, noise reduction, contrast enhancement, and segmentation substantially improve data consistency, enabling models to better capture disease- specific patterns. Furthermore, advanced feature extraction approaches—including gradient descriptors, texture analysis, and moment-based features—provide deeper structural insights that strengthen model reliability across diverse disease categories.

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compared to standard pattern detection techniques. It employs an end-to-end structure to simplify the detecting procedure. In this study, we compared the best classifier for effectively classifying tomato leaf disease with an accuracy of 96.735 percent.

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