International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. IV, No. 01, pp. 39-49, January

Towards Sustainable Crop Protection: Deep Learning-Based Tomato Leaf Disease Detection with AlexNet

P. Karputha Pandi[1*], A. Darcy Gnana Jegha[2]

[1*]Department of Electrical and Electronics Engineering, Assistant Professor, Erode Senguthar Engineering College, Perundurai.
[2]Department of Electrical and Electronics Engineering, PSN Institute of Technology and Science, Tirunelveli, India.

***Corresponding Author E-mail: karputhapandi15102@gmail.com**

ABSTRACT: Ensuring crop health and increasing agricultural productivity depend on the diagnosis of leaf diseases. This research work offers a sophisticated deep learning-based strategy for automatically classifying leaf diseases. To improve accuracy, the proposed method combines features from both classification and feature extraction. Research findings indicate that the model outperforms traditional models like CNN, AlexNet, and MobileNet V2 with a high classification accuracy of 95%. The confusion matrix and ROC curve demonstrate little misclassification and good class separation, confirming the model's efficacy. Additionally, high precision, recall, and F1-scores across multiple disease categories confirm balanced performance. Training and validation trends indicate effective learning, with minor overfitting be addressed using dropout regularization and data augmentation. The findings establish proposed model as a trustworthy and efficient solution for automated leaf disease diagnosis in precision agriculture.

Keywords: Tomato leaf disease, Grayscale Conversion, Median Filtering, Fuzzy C Means, Hough Transform and Alex Net.

1. Introduction

The most widely grown vegetable is the Tomato (or) Solanum lycopersicum, which produces 180.64 million metric tons a year, according to latest data, valued at around 808.1 billion US dollars for its nutritional value, tomatoes are an essential crop that supports the livelihoods of farmers worldwide. However, the growth and quality of tomatoes are frequently challenged by different leaf diseases, which have a major impact on quality and productivity, thereby reducing productivity [1, 2]. Detecting these diseases is a key focus in precise agriculture, where advancements in image analysis are being utilized to identify plant infections. Historically, disease detection has relied on visual assessments by experts, by evaluating the severity of symptoms in plant tissues. Some common diseases that affect are bacterial spots, late blight, early blight, target spots, two-spotted spider mites, mosaic virus, yellow leaf curl virus, and septoria leaf spots on tomato leaves. [3, 4].Traditional disease detection methods, like manual inspection and chemical analysis, are often error-prone and inefficient. The shortage of agricultural experts, especially in rural areas, delays disease identification, reducing crop yield and overall productivity [5]. Through leaf image analysis, the application of computer vision and image processing techniques to diagnose tomato plant diseases has increased recently. Preprocessing enhances tomato leaf disease detection by refining image quality for accurate analysis. Traditional methods use techniques like noise reduction and contrast enhancement, while modern approaches integrate deep learning for improved feature extraction. These steps optimize input data, ensuring precise disease classification [6, 7].The process of tomato leaf disease detection involves three crucial processes: classification, feature extraction, and segmentation. Techniques for segmentation include edge detection, thresholding, and clustering-based approaches like fuzzy c-means and k-mean, help isolate diseased regions in leaf images. Traditional approaches rely on manual segmentation, while deep learning-based methods, including CNNs and U-Net, provide more accurate and automated segmentation [8, 9]. Feature extraction involves analyzing leaf characteristics, utilizing handmade techniques like GLCM and LBP, which include color, texture, and shape. In contrast, deep learning models automatically learn features, improving detection accuracy [10, 11]. Classification methods categorize diseases based on extracted features. Conventional classifiers, such as SVM and Random Forest, are widely used, while modern deep learning models, including CNNs and hybrid architectures, offer enhanced performance and reliability [12, 13].With the increasing availability of high-resolution imaging and computational power, deep learning models are becoming more efficient in real-time disease identification. These models process enormous volumes of picture data, enabling the quick and precise classification of plant diseases, reducing the dependency on human expertise [14, 15]. Furthermore, combining disease detection frameworks with IoT-enabled smart farming systems improves monitoring and decision-making, which raises agricultural sustainability and production. The contribution of this paper is defined as follows.

- Implementing preprocessing techniques, including grayscale conversion and median filtering, to enhance image quality for accurate tomato leaf disease detection.
- Fuzzy C-Means (FCM) enables precise segmentation of diseased regions in tomato leaves by assigning membership values to each pixel, ensuring smooth boundaries and improved detection even in noisy images.
- Enhancing the detection of disease-specific edges and shapes by improving the identification of infected regions using the Hough Transform.
- Alex Net is incorporated for accurate classification of tomato leaf disease.

The structure of paper is defined as follows Section 2 reviews the relevant literature. Section 3 describes the proposed methodology of tomato leaf disease. Section 4 presents the findings based on diseases in tomato leaf. Section 5 summarizes the conclusions.

2. Literature Review

S. Mumtaz *et al*, (2025) [16] have employed a Gaussian distribution-based classifier for leaf classification as well as a Random Forest classifier. The Gaussian classifier offers high accuracy 92% due to its probabilistic approach, making it effective for well-distributed data. However, it struggles with non-Gaussian data distributions. The Random Forest classifier, achieving 84.63% accuracy on the Leaf Dataset, is robust against over fitting and handles diverse data well. However, it be computationally intensive.

L. K. Ndovie *et al*, (2024) [17] have utilized MobileNetV3 and CNN classifying tomato leaf disease. MobileNetV3, a lightweight deep learning model, achieves high accuracy 92.59% on Plant Village dataset due to its efficiency and optimized architecture. However, it struggles with generalization in real-world scenarios, yielding only 9.2% accuracy on field data. Similarly, CNN performs well on the Plant Village dataset but fails in practical conditions, indicating over fitting to training data.

K. Roy *et al*, (2023) [18] have studied Faster Region-Based CNN (F-RCNN) for tomato leaf disease detection. F-RCNN is highly effective in object detection, achieving 99.60% classification accuracy and 98.55% average precision. Its strength lies in its ability to accurately localize and classify diseases, making it suitable for real-world agricultural applications. However, F-RCNN is computationally expensive and requires substantial training data.

Paul, S. G *et al*, (2023) [19] have employed a custom CNN alongside transfer learning models VGG-16 and VGG-19 for tomato leaf disease classification. The custom CNN achieves the highest accuracy of 95%, benefiting from optimized parameters and data augmentation. Its lightweight nature makes it efficient for deployment in web and mobile applications. However, CNN models may require extensive labelled data for effective training. VGG-16 and VGG-19 offer robust feature extraction but are computationally demanding. While the work improves disease identification accuracy, further enhancements in model generalization and adaptability to real-world conditions are necessary for broader agricultural applications.

M. B. Hasan *et al*, (2022) [20] have employed a transfer learning-based classifier using a proprietary classifier network in conjunction with a pretrained MobileNetV2 architecture, tomato leaf disease detection. MobileNetV2 is efficient, achieving 99.30% accuracy while making it ideal for low-end devices. The model benefits from enhanced image preprocessing and runtime augmentation, improving generalization and reducing data leakage. However, MobileNetV2 may struggle with complex feature extraction compared to deeper networks.To improve performance this research proposes AlexNet for effective classification increasing for attaining improved accuracy and make the model more adaptable in detecting tomato leaf diseases.

3. Proposed Methodology

Figure 1's proposed system block diagram represents framework of a leaf disease detection system that integrates deep learning methods for image processing for accurate classification. The process begins with the preprocessing stage, where the input dataset undergoes grayscale conversion and median filtering to enhance image quality and eliminate noise.

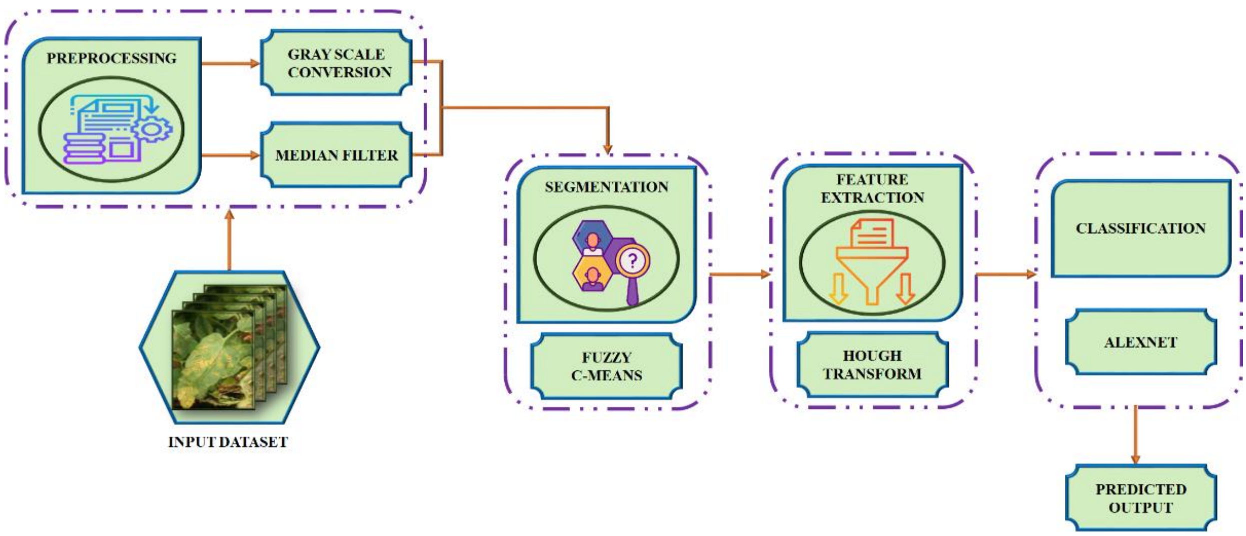

Figure 1: *The flowchart displays the Proposed Methodology of the tomato leaf disease*

Following preprocessing, the segmentation phase utilizes Fuzzy C-Means clustering algorithm to accurately segment the diseased regions of leaf. Next, feature extraction is applied to the segmented images using the Hough Transform, which identifies relevant features necessary for classification. In the classification stage, the extracted features are processed by the Alex Net to categorize the leaf images based on disease types. The final step generates the predicted output, providing an accurate classification of the detected leaf disease.

3.1. Preprocessing

The preprocessing stage is essential for enhancing image quality and ensuring accurate disease detection in tomato leaves. This methodology incorporates grayscale conversion and median filtering to simplify feature extraction and improve noise reduction. The following steps outline the proposed approach:

3.1.1 Grayscale Conversion

To reduce computational complexity and enhance contrast, the captured RGB images are converted into grayscale. This process eliminates colour information while preserving essential texture and intensity features. Each pixel's grayscale value is calculated using a weighted sum method:

$$I = 0.299R + 0.587G + 0.114B \qquad (1)$$

Where R, G and B represent the red, green, and blue components of the image, respectively. Transformation results in a single-channel image that simplifies further processing.

3.1.2 Noise Reduction Using Median Filtering

A median filter, also known as median blur [21], helps reduce noise in images by changing the value of each pixel to the neighboring pixels' median. In contrast to other blurring methods, it preserves edges while smoothing the image. The equation for median blur is given as:

$$\mathrm{I}_{\mathrm{out}}(\mathrm{x},\mathrm{y}) = \mathrm{test}_{\mathrm{median}}\big(\mathrm{I}_{\mathrm{in}}(\mathrm{x}-\mathrm{k}:\mathrm{x}+\mathrm{k},\mathrm{y}-\mathrm{k}:\mathrm{y}+\mathrm{k})\big) \qquad (2)$$

In the median filter, k represents filter kernel's radius, I_{in} is the original image, and $\mathrm{I}_{\mathrm{out}}$ is the filtered image. The coordinates (x, y) indicate the pixel being processed. The $test_{median}()$ function calculates the neighbouring pixels' median value to replace the original pixel value. Grayscale conversion simplifies image processing by reducing colour complexity and enhancing contrast for better feature extraction. The median filter removes noise while preserving edges, improving image quality for accurate segmentation.

3.2 Fuzzy C-Means Clustering for Segmentation

The FCM [22] model, introduced by Dunn, is an unsupervised classification method based on fuzzy logic. FCM allows data points to be partially affiliated with multiple clusters, as opposed to the conventional K-means approach, which allocates each data point to a single cluster. Equation (3) calculates the cluster centers

$$\mathrm{d_j} = \frac{\sum_{k=1}^{M} \mathrm{v_j^n{,}_k y_k}}{\sum_{k=1}^{M} \mathrm{v_j^n{,}_k}} \qquad (3)$$

The dataset contains M data points, where each kth pixel has a degree of membership. The fuzzifier, denoted as $\mathrm{n}(\mathrm{n} > 1)$, is greater than 1. The k^{th} data point is represented as $\mathrm{y_k}$, and Equation (4) defines the formula for $\mathrm{v_{j,k}}$.

$$\mathrm{v_{j,k}} = \frac{1}{\sum_{L=1}^{md} \frac{c_{j,k}^{2/(n-1)}}{c_{j,k}}} \qquad (4)$$

$$\mathrm{k} = \sum_{k=1}^{M} \sum_{j=1}^{md} \mathrm{v_{j,k}^n} * \mathrm{c}^2\big(\mathrm{y_k}, \mathrm{d_j}\big) \qquad (5)$$

Equation (6) under constraints

$$\begin{cases} \forall k \in [1, M], \forall k \in [1, md] : v_{j,k} \in [0,1] \\ \forall k \in [1, M] : \sum_{j=1}^{md} v_{j,k} = 1 \end{cases} \qquad (6)$$

The dataset consists of M data points, where each pixel has a membership degree$\mathrm{v_{j,k}}$. The distance between the jth cluster and the kth pixel is given by $\mathrm{c}^2\big(\mathrm{y_k}, \mathrm{d_j}\big)$. The fuzziness parameter n ranges from $(1 < \mathrm{n} \leq \infty)$. The optimal cluster centers help in segmenting the diseased regions in the leaf image. Algorithm 1 provides the pseudocode for the FCM method.

Table 1: *Pseucode of the FCM method*

Algorithm: FCM

Start: Initialize the plant image, n degree of fuzziness$(n > 1)$, error(ε), and the number of clusters c with the cluster centers$\left(d_j^{(0)}\right)$

$k = 1$

Do again

The centers$\left(d_j^{(i-1)}\right)$ compute a membership $\left(v_{j,k}^{(i)}\right)$

$$v_{j,k} = \frac{1}{\sum_{L=1}^{md} \frac{c_{j,k}^{2/(n-1)}}{c_{j,k}}}$$

Use $v_{j,k}^{(i)}$ to update the centred$d_j^{(i)}$

$$d_j = \frac{\sum_{k=1}^{M} V_{j,k}^{n} y_k}{\sum_{k=1}^{M} V_{j,k}^{n}}$$

Until $C_j^{(i)} - C_j^{(i+1)} < \varepsilon$

Return $d_j^{(i)}$(optimal cluster centers selection)

FCM segmentation is used to accurately group similar pixels by allowing partial membership in multiple clusters, making it more flexible than hard clustering. This improves region separation and enhances feature extraction by ensuring relevant data is preserved.

3.3 Feature Extraction

The Hough Transform is an effective feature extraction technique used to identify geometric shapes such as lines and curves in tomato leaf images. It helps in detecting disease patterns, including leaf spots and vein distortions, by identifying structural features within the affected regions. The pre-processed image's geometric features are extracted using the Hough Transform.:

- Edge Detection: The reprocessed image undergoes edge detection to enhance disease-related structures.
- Hough Space Mapping: Pixels along detected edges are transformed into a parameter space where geometric shapes like lines and circles be identified.
- Shape Detection: The algorithm detects key features such as circular lesions using the circular Hough transform and linear vein distortions, which are crucial indicators of disease.

The extracted features, such as line orientations, spot shapes, and edge distributions, are analysed to determine disease severity. These features are used as input for classification models.

3.4 Alex Net classification

The AlexNet architecture, which initially had eleven layers, served as the foundation for the CNN [23] used in the present research. Nevertheless, the architecture has been altered by lowering the number of layers. The modified AlexNet architecture used in the present research consists of six layers, including three convolutional layers, three fully linked levels, and an output layer.

The RGB-formatted input image utilized in this research has a resolution of 64 × 64 pixels. 32 filters with a 3 × 3 kernel size are used by the first convolutional layer to extract significant information from the input image. This layer is made non-linear by using the Rectified Linear Unit (ReLU) activation function, which improves the model's capacity to recognize intricate patterns. Equation (7) provides ReLU activation function in mathematical form.

$$f(x) = \max(0, x) \tag{7}$$

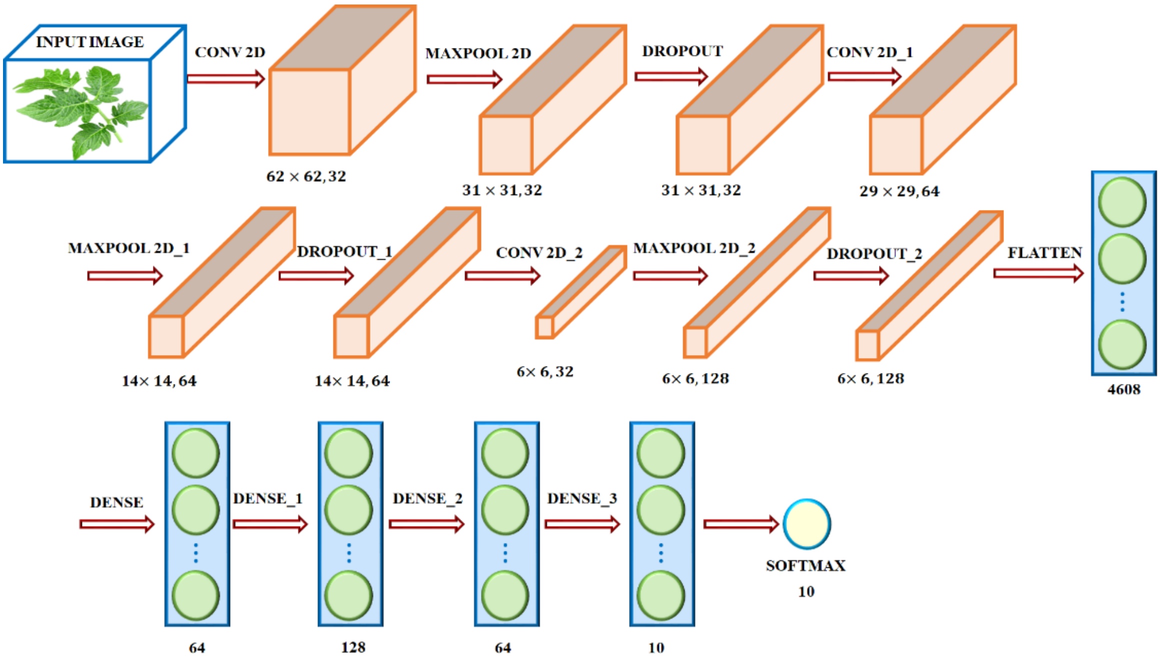

Figure 2: *The architecture of AlexNet*

The signal is transformed using a non-linear activation function before being sent to the following layer. Positive values stay the same while values below zero are set to zero when it operates with a threshold of $\mathbf{0}$. After the initial Conv2D layer, there is an initial max pooling layer with a pooling size of $\mathbf{2} \times \mathbf{2}$ and a dropout rate of 0.2. This second convolutional layer uses the ReLU activation function with 64 filters and a $\mathbf{3} \times \mathbf{3}$ kernel size. The second convolution layer uses the output from the first convolution layer and the pooling layer that came before it as inputs. The second max pooling layer has a $\mathbf{2} \times \mathbf{2}$ pooling size and a 0.2 dropout rate. Next is a third convolution layer with a $\mathbf{3} \times \mathbf{3}$ kernel size and 64 filters that uses the ReLU activation function. The output from the pooling layer and the second convolution layer is sent to the third convolutional layer. The pooling size of the second max pooling layer is$\mathbf{2} \times \mathbf{2}$, and its dropout rate is higher at 0.4. Lastly, the third convolution layer uses 128 filters with a $\mathbf{3} \times \mathbf{3}$ kernel size to apply the ReLU activation function. Softmax activation function is used to normalize the output of the next layer, ensuring that predicted values fall within the range$[0,1]$, with their sum equal to 1. Equation (6) provides the mathematical representation of the Softmax function, where j is the index of each element z and N is the total number of elements$z$. Equation (8) formulates the Softmax function, which is used to assign probabilities to each class, with the highest probability determining the predicted class.

$$\sigma(z)_j = \frac{e^{Zj}}{\sum_{k=1}^{N} e^{Zk}}, j = \{1,2, \cdots, N\} \quad (8)$$

The architecture utilized in this research was established through a series of experimental evaluations, focusing on optimizing the number of layers to identify the most effective CNN model. These experiments were conducted to enhance performance and ensure the best configuration for the given task.

4. Results and Discussion

The proposed work for classification consisting 16027 images of tomato diseases. After that, 20% is set up for testing and 80% is allocated for training. Manual feature selection is no longer necessary thanks to convolutional learning models for deep learning that automatically extract features. To evaluate the effectiveness of these procedures, key metrics such F1-score, recall, accuracy, and precision were used.

Table 2: *Explains the equations for finding true and false positive values*

Performance Metrics	Formulae
Accuracy	$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%$
Precision (P):	$Precision = \frac{TP}{TP + FP} \times 100\%$
Recall (R):	$Recall = \frac{TP}{TP + FN} \times 100\%$
F1-score (F1):	$F1 = \frac{2PR}{P + R} \times 100\%$

Positive cases that are accurately recognized are referred to as True Positives (TP), while False Positive (FP) occurs when a positive case is wrongly predicted. True Negative (TN) represents correctly identified negative cases, and False Negative (FN) happens when a negative case is incorrectly classified.

Table 3: *Number of Test and Train Images*

Leaf Type	Data Count
bacterial-spot	444 test data
bacterial-spot	1679 train data
healthy	444 test data
healthy	1883 train data
late blight	444 test data
late blight	2093 train data
septoria leaf spot	444 test data
septoria leaf spot	1327 train data
target spot	444 test data
target spot	1110 train data
Two spotted spider mite	444 test data
Two spotted spider mite	1232 train data
yellow leaf curl virus	444 test data
yellow leaf curl virus	3595 train data

Table 3 shows the quantity of data required for the process, and the results illustrate how well the proposed approach performs in correctly diagnosing various leaf diseases. The discussion highlights model's performance, comparing its accuracy with existing methods to validate its reliability.

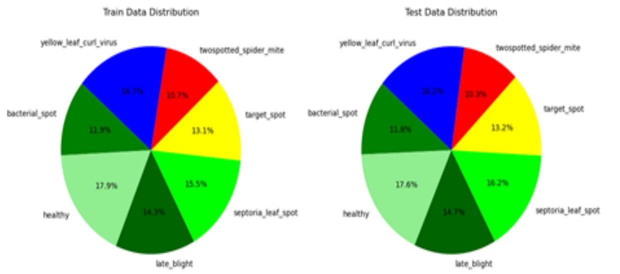

Figure 3: *Test and Train distribution*

To guarantee an efficient model, Figure 3 separates the dataset into sets of evaluation and learning into test and train, pie charts show the percentage of each leaf disease category in both datasets. Yellow leaf curl virus has the highest proportion, while other diseases like bacterial spot, septoria leaf spot, and target spot more evenly distributed. This balanced data distribution helps the model learn different disease patterns and improves its accuracy in classification.

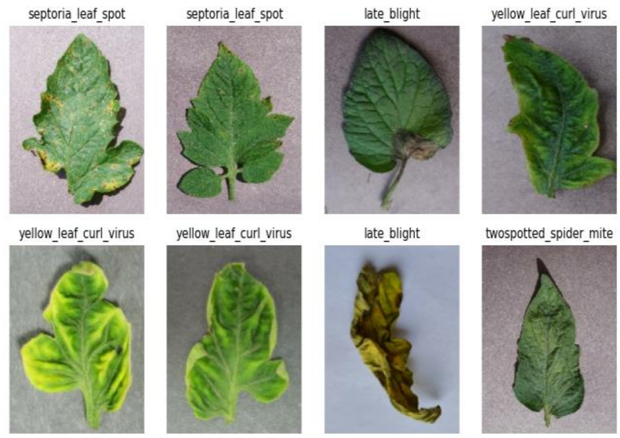

Figure 4: *Random Number of Leaf Images*

The Figure 4 shows various diseased leaves affected by Late blight, septoria leaf spot, two-spotted spider mite, and yellow leaf curl virus, each displaying distinct symptoms such as spots, discoloration, curling, and damage.

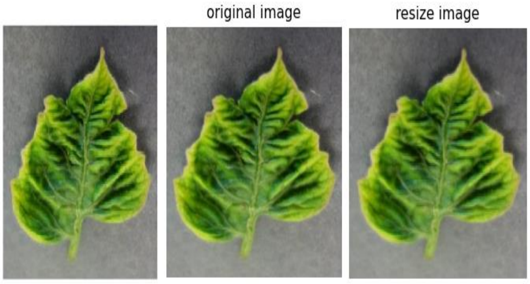

Figure 5: *Preprocessed Output Image*

The figure 5 showcases various image processing techniques applied to a leaf, including resizing to adjust dimensions, grayscale conversion to remove color while preserving texture, and median filtering to reduce noise and enhance image smoothness.

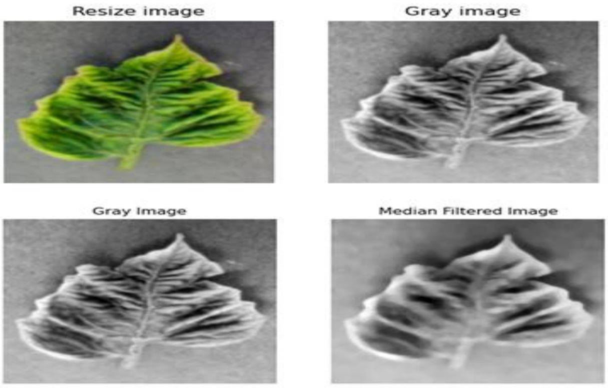

Figure 6: GrayScale Conversion and Median Filter Image

The Figure 6 showcases various image processing techniques applied to a leaf, including resizing to adjust dimensions, grayscale conversion to remove color while preserving texture, and median filtering to reduce noise and enhance image smoothness.

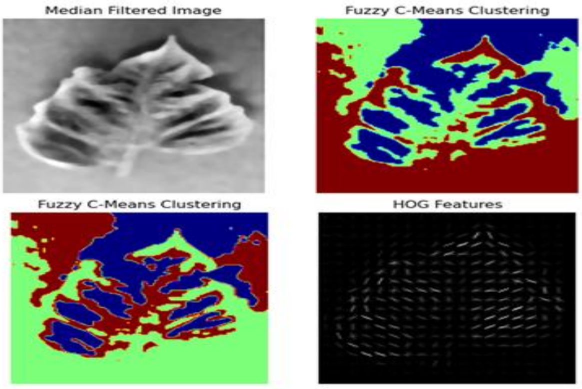

Figure7: *Median filter image with Fuzzy C means and HOG feature*

The Figure 7 showcases different image processing techniques applied to a leaf-like structure, including median filtering for noise reduction, Fuzzy C-Means clustering for segmentation as well as feature extraction using the Histogram of Oriented Gradients (HOG).

Table 4: *Shows the values of Accuracy, precision, recall and F1score.*

Classification Report				
	Precision	**Recall**	**F1-Score**	**Support**
Bacterial-Spot	0.98	0.96	0.97	444
Healthy	0.98	0.97	0.98	444
Late Blight	0.95	0.97	0.96	444
Septoria Leaf Spot	0.98	0.91	0.94	444
Target Spot	0.91	0.94	0.93	444
Two spotted Spider Mite	0.96	0.93	0.94	444
Yellow Leaf Curl Virus	0.94	0.99	0.97	444
Accuracy			**0.95**	**3108**
Macro avg	0.96	0.95	0.95	3108
Weighted avg	0.96	0.95	0.95	3108

The classification report shows that the model performs well in identifying different leaf conditions, with precision between 0.91 and 0.98, F1-scores between 0.93 and 0.98, and recall between 0.91 and 0.99. The overall accuracy is 95%, while the F1-score weighted and macro averages, precision, and recall are all 0.95, indicating balanced and reliable performance across 3,108 test samples in table 4.

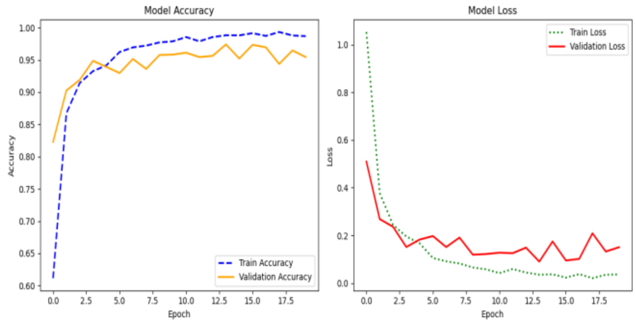

Figure 8: *Model Accuracy and Loss*

The classification report presented in Figure 8 shows that the model performs well in identifying different leaf conditions, with precision between 0.91 and 0.98, F1-scores range from 0.93 to 0.98, and recall range from 0.91 to 0.99. The total accuracy is 95%, with weighted averages of 0.95 for precision, recall, and F1-score., indicating balanced and reliable performance across 3,108 test samples.

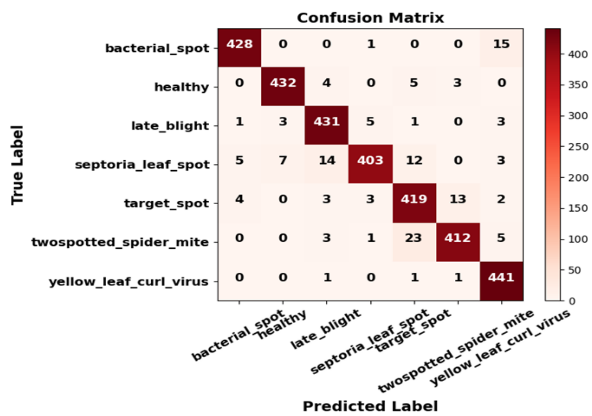

Figure 9: *Confusion Matrix*

The confusion matrix displays model's classification results for different leaf diseases, in Figure 9. The model correctly predicted 428 bacterial spot**,** 432 healthy, and 431 late blight cases. Some errors occurred, such as 15 bacterial spot cases being misclassified and 23 two spotted spider mite cases being mistaken for other categories. Overall, the model shows strong accuracy with a few misclassifications.

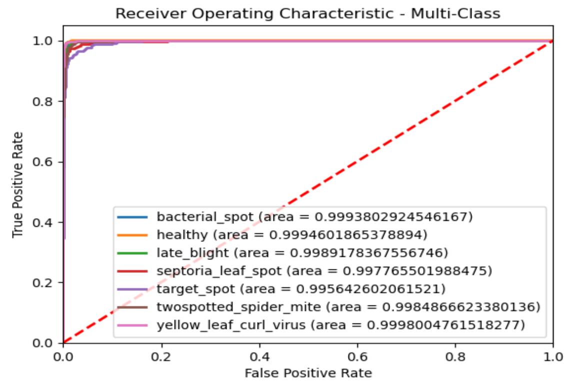

Figure 10: *ROC Characteristics of Multiclass Disease*

Figure 10's Receiver Operating Characteristic (ROC) curve displays the model's performance in distinguishing between different leaf diseases. Each disease has an AUC value close to 1.0, indicating high classification accuracy. The model effectively differentiates between disease categories with minimal false positives.

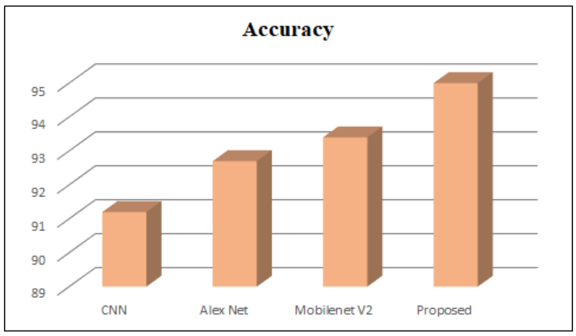

Figure 11: *Comparison of Accuracy*

Figure 11 shows a bar chart that contrasts the accuracy of various models. CNN has lowest accuracy, slightly above 91%, while Alex Net performs better, reaching around 93%. Mobile Net V2 achieves a slightly higher accuracy, close to 94%. The proposed model outperforms all, reaching approximately 95.5%, indicating its improved performance.

5. Conclusion

The proposed method classifies leaf diseases with superior performance, achieving an overall accuracy of 95%. The categorization report attests to all categories' strong F1-scores, recall, and precision, indicating balanced and reliable predictions. The ROC curve further validates the model's effectiveness, with AUC values close to 1, signifying strong class separation. The confusion matrix highlights minimal misclassifications, signifying the model effectively captures distinguishing features. Compared to CNN, AlexNet, and Mobile Net V2, the proposed method achieves the highest accuracy, showcasing the impact of advanced architecture and optimization techniques. Training and validation trends confirm stable learning, though slight overfitting be addressed with techniques like dropout and data augmentation. Future enhancements may include refining feature extraction, optimizing hyper parameters, and integrating advanced deep learning methods to enhance classification performance even more. Overall, results establish the proposed model as a reliable solution for automated leaf disease diagnosis.

References

1. Changjian Zhou; Sihan Zhou; Jinge Xing; Jia Song, Year: 2021, "Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network", in IEEE Access, Vol. 9, pp. 28822-28831.

2. Emre Özbılge; Mehtap Köse Ulukök; Önsen Toygar; Ebru Ozbılge, Year: 2022, "Tomato disease recognition using a compact convolutional neural network", IEEE Access10, pp. 77213-77224.

3. Sami Ur Rahman; Fakhre Alam; Niaz Ahmad; Shakil Arshad, Year: 2023, "Image processing based system for the detection, identification and treatment of tomato leaf diseases", Multimedia Tools and Applications 82, No: 6, pp. 9431-9445.

4. Kyamelia Roy; Sheli Sinha Chaudhuri; Jaroslav Frnda; Srijita Bandopadhyay; Ishan Jyoti Ray; Soumen Banerjee; Jan Nedoma, Year: 2023, "Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA DeepNet", in IEEE Access, Vol: 11, pp. 14983-15001.

5. Muhammad Umar; Saud Altaf; Shafiq Ahmad; Haitham Mahmoud; Adamali Shah Noor Mohamed; Rashid Ayub, Year:2024, "Precision Agriculture through Deep Learning: Tomato Plant Multiple Diseases Recognition with CNN and Improved yolov7", in IEEE Access, Vol: 12, pp. 49167-49183.

6. Khalid M Hosny; Walaa M. El-Hady; Farid M. Samy; Eleni Vrochidou; George A. Papakostas, Year: 2023, "Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern", in IEEE Access, Vol. 11; pp. 62307-62317.

7. Sabbir Ahmed; Md Bakhtiar Hasan; Tasnim Ahmed; Md Redwan Karim Sony; M. H. Kabir, Year: 2022, "Less is More: Lighter and Faster Deep Neural Architecture for Tomato Leaf Disease Classification", in IEEE Access, Vol: 10, pp. 68868-68884.

8. Kandarpa Kumar Sarma; Kunal Kingkar Das; Vikash Mishra; Samadrita Bhuiya; Dmitrii Kaplun, Year: 2022, "Learning Aided System for Agriculture Monitoring Designed Using Image Processing and IoT-CNN", in IEEE Access, Vol: 10, pp. 41525-41536.

9. Kyamelia Roy; Sheli Sinha Chaudhuri; Jaroslav Frnda; Srijita Bandopadhyay; Ishan Jyoti Ray; Soumen Banerjee; Jan Nedoma, Year: 2023, "Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA DeepNet", Vol. 11, pp. 14983-15001.

10. Khalid M. Hosny; Walaa M. El-Hady; Farid M. Samy; Eleni Vrochidou; George A. Papakostas, Year:2023, " Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern", Vol: 11, pp. 62307-62317.

11. Abdelmalik Ouamane; Ammar Chouchane; Yassine Himeur; Abderrazak Debilou ; Abbes Amira; Shadi Atalla; Wathiq Mansoor; Hussain Al Ahmad, Year:2024, "Knowledge Pre-Trained CNN-Based Tensor Subspace Learning for Tomato Leaf Diseases Detection", Vol: 12, pp. 168283-168302.

12. Hasibul Islam Peyal; Md Nahiduzzaman; Md Abu Hanif Pramanik; Md Khalid Syfullah; Saleh Mohammed Shahriar; Abida Sultana; Mominul Ahsan; Julfikar Haider; Amith Khandakar; Muhammad EH Chowdhury, Year:2023, "Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture", Vol: 11, pp. 110627-110643.

13. Mahmoud H Alnamoly; Anar A. Hady; Sherine M. Abd El-Kader; Ibrahim El-Henawy, Year: 2024, "FL-ToLeD: An Improved Lightweight Attention Convolutional Neural Network Model for Tomato Leaf Diseases Classification for Low-End Devices", Vol: 12, pp. 73561-73580.

14. Yang Wu; Xian Feng; Guojun Chen, Year: 2022, ''Plant leaf diseases fine-grained categorization using convolutional neural networks,'' IEEE Access, Vol: 10, pp. 41087–41096.

15. Changjian Zhou; Sihan Zhou; JingeXing; Jia Song, Year: 2021, "Tomato leaf disease identification by restructured deep residual dense network", IEEE Access9, pp. 28822-28831.

16. Sara Mumtaz; Shabbab Algamdi; Haifa F.Alhasson; Dina Abdulaziz Alhammadi; Ahmad Jalal; Hui Liu, Year:2025, "Leaf Classification for Sustainable Agriculture and In-Depth Species Analysis", in IEEE Access, Vol: 13, pp. 17043-17053.

17. Kyamelia Roy; Sheli Sinha Chaudhuri; Jaroslav Frnda; Srijita Bandopadhyay; Ishan Jyoti Ray; Soumen Banerjee; Jan Nedoma, Year: 2023, "Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA DeepNet", Vol. 11, pp. 14983-15001.

18.Showmick Guha Paul; Al Amin Biswas; Arpa Saha; Md Sabab Zulfiker; Nadia Afrin Ritu; Ifrat Zahan; Mushfiqur Rahman; Mohammad Ashraful Islam, Year: 2023, "A real-time application-based convolutional neural network approach for tomato leaf disease classification",Array 19, pp. 100313

19. Md Bakhtiar Hasan; Tasnim Ahmed; Md Redwan Karim Sony; Md Hasanul Kabir, Year: 2022, "Less is More: Lighter and Faster Deep Neural Architecture for Tomato Leaf Disease Classification", in IEEE Access, Vol: 10, pp. 68868-68884.

20. Md Iqbal Hossain; Sohely Jahan; Md Rashid Al Asif; Md Samsuddoha; Kawsar Ahmed, Year: 2023, "Detecting tomato leaf diseases by image processing through deep convolutional neural networks," Smart Agricultural Technology 5, pp. 100301.

21. A. Umamageswari; N. BharathirajaIrene; D. Shiny Irene, Year: 2023, "A novel fuzzy C-means based chameleon swarm algorithm for segmentation and progressive neural architecture search for plant disease classification", ICT Express 9, No: 2, pp. 160-167.

22. H. C.Chen; A. M. Widodo; A.Wisnujati; M. Rahaman; J. C. W. Lin; L. Chen; C. E. Weng, Year: 2022, "AlexNet convolutional neural network for disease detection and classification of tomato leaf", Electronics 11, pp. 951.

23. Mohit Agarwal; Abhishek Singh; Siddhartha Arjaria; Amit Sinha; Suneet Gupta, Year: 2020, "ToLeD: Tomato leaf disease detection using convolution neural network", Procedia Computer Science, 167, pp. 293-301.