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Research paper

Machine Learning Based Novel Hybrid Approach for Plant Leaf Disease Detection and Feature Extraction Along with Statistical Analysis Using Big Data

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Abstract

Plant diseases pose a serious threat to global food security and agricultural productivity [29]. They are commonly caused by pathogens such as viruses, bacteria, fungi, insects, rusts, and nematodes, with most infections affecting the stem and leaves of plants [2]. To address these challenges, researchers have applied various approaches including deep learning methods, image processing techniques, and machine learning algorithms. This study focuses on two main techniques: Canny Edge Detection (CED) and color-based feature extraction, selected after reviewing 43 research articles published in reputed journals. Additionally, Long Short-Term Memory (LSTM) networks were integrated with Canny Edge Detection to enable disease detection in videos and time-series data. For experimental evaluation, leaf samples from lady's finger, brinjal, and tomato were tested. The proposed model demonstrated high accuracy: 99.55%, 99.10%, and 98.7% using Canny Edge Detection; 99.62%, 99.23%, and 99.13% with color-based feature extraction; and 99.48%, 99.50%, and 99.39% using the hybrid model. This digital plant disease detection framework can provide significant support to farmers and cultivators by enabling timely and accurate identification of crop diseases.

Keywords: *Canny Edge Detection; Long Short Term Memory (LSTM); Plant Disease Detection; Colour Feature Extraction.*

1. Introduction

Plants are essential to human survival as they provide food, making agriculture one of the most vital sectors [7]. In India, agriculture serves as the primary source of livelihood, especially in rural areas where the majority of the population depends on it [4]. Around 70% of India's workforce is engaged in agriculture, highlighting its role as an agricultural nation [5]. The agricultural sector also makes a significant contribution to the Gross Domestic Product (GDP) of the country [7]. Agricultural research aims to improve food quality and productivity while reducing costs and increasing profitability [1].

Digital image processing has emerged as an important tool in agriculture, particularly for disease detection [2]. Plant diseases have a direct impact on global food security and agricultural productivity, often causing substantial yield and financial losses in international trade [29]. Digital imaging techniques have proven effective in diagnosing plant diseases by identifying early symptoms during crop growth [2].

Most plant diseases affect leaves and stems, and they are caused by pathogens such as fungi, bacteria, viruses, insects, rust, and nematodes [2]. Leaf diseases, in particular, threaten crop quality, yield, and overall growth [23]. Early detection and effective management are therefore critical to sustaining healthy crops and reducing agricultural losses [23]. In this context, feature extraction plays a key role, as it involves identifying and retrieving relevant information from pre-processed images to support accurate leaf disease detection [23].

1.1. Objective of the paper

- The first objective of the paper is designed as the plant leaf disease detection-based survey through the papers that have been published in refereed and reputed journals.
- The plant leaf disease identification method has been implemented by using Canny Edge detection.
- According to the study, the Colour-based Feature Extraction method has been used to identify the plant leaf detection.
- The Hybrid model has been designed with the combination of Canny Edge detection (CNN) and Long Short Term Memory (LSTM).

- The proposed model has been tested by using disease-affected Lady's Finger, Brinjal and Tomato leaves. Then the accuracy has evaluated and tabulated by using descriptive statistical model which has been generated by Microsoft Excel.

2. Literature Review

Studies on plant disease detection highlight the transition from traditional observation to automated, machine learning–based methods. Vishnu and Ranjith Ram (2015) proposed an image-processing approach using segmentation, texture features, and neural networks, while Rajneet Kaur and Manjeet Kaur (2017) recommended KNN over neural networks and compared it with SVM. Hailay Beyene et al. (2018) reviewed ANN and CNN for early detection, and Kanaka Durga and Anuradha (2019) applied HOG with SVM and ANN for tomato and maize disease detection, sharing results with farmers. Deepa et al. (2019) introduced an Android app achieving over 99% accuracy in leaf disease diagnosis. Nilay Ganatra and Atul Patel (2020) used Random Forest with 73.38% accuracy but noted performance drops with larger datasets.

Hardikkumar Jayswal and Jitendra Chaudhari (2020) highlighted deep learning's superiority over traditional methods and stressed the need for better datasets. Similarly, Sapna Nigam and Rajni Jain (2020) emphasized early detection, comparing deep learning with conventional approaches in the Indian context. Expanding beyond agriculture, Bahzad Taha Jijo and Adnan Mohsin Abdulazeez (2021) reviewed decision tree classifiers (ID3, C4.5, CART), reporting accuracies up to 99.93%. Finally, Sreya John and Arul Leena Rose (2021) reviewed automated detection systems using machine learning and image processing, noting their effectiveness over traditional methods in improving crop health.

Greeshma (2021) proposed a CNN-based Plant Disease Recognition Model that used edge detection and data augmentation, achieving higher accuracy than traditional methods, while Sakshi Mangal and Pratiksha Meshram (2021) applied image processing with Laplacian filters and CNNs, highlighting the economic importance of early disease detection in India where pests cause 15.7% of annual crop losses. Sona Vijayan and Prameeja Vimal (2021) demonstrated that KNN outperformed Naïve Bayes in detecting tomato leaf diseases, achieving 80% accuracy, whereas Dmitry Malakhov (2022) used satellite, climate, and crop rotation data to predict fungal outbreaks like Septoria leaf blotch in Kazakhstan through probability mapping.

Jackulin and Murugavalli (2022) emphasized the role of deep learning in addressing gaps in current methods for detecting bacterial, fungal, and viral crop diseases, while Anwar Abdullah Alatawi et al. (2022) applied a VGG-16 model on 15,915 images to classify 19 plant diseases with 95.2% accuracy, though performance was limited by lighting and background complexity. Similarly, Pallepati Vasavi et al. (2022) reviewed machine learning approaches, suggesting algorithms for mobile applications to enhance real-time detection, and Shakir Mahmood Abas (2022) introduced a modified Faster R-CNN with a custom pre-trained CNN that improved WBC classification speed and accuracy for leukemia diagnosis. In cotton disease detection, Anitharani (2022) reviewed techniques such as SVM, Random Forest, CNN with K-means clustering, and ANN, showing ANN's effectiveness, while Gaurav Shrivastava and Harish Patidar (2022) developed a decision support system for rice farmers, finding ANN superior to SVM in accuracy and stressing its contribution to food security.

Gautam Lambe et al. (2022) applied CNN models on single-leaf images for disease identification, aiming to reduce pesticide use, improve quality, and minimize manual effort. Mahmudul Hassan et al. (2022) compared handcrafted and deep learning methods, noting that models like GoogleNet and InceptionV3 achieve higher accuracy but face real-world challenges, highlighting the need for preprocessing, segmentation, and larger datasets for mobile use. Similarly, Aditi Patil et al. (2022) proposed a CNN-based system integrated into an Android app for farmers, while Chinna Rao et al. (2023) showed that CNN models achieved 97.71% accuracy in leaf classification compared to 80% with SVM, suggesting transfer learning for further improvement.

In grape disease detection, Prasad and Blessed Prince (2023) found that HOG with SVM outperformed other combinations, offering reliable diagnosis, and Shivani Dombale et al. (2023) demonstrated that image processing with triangle threshold segmentation effectively supports disease management of Rust and Black Rot. Suneetha et al. (2023) highlighted the role of MATLAB-based image processing for faster detection, suggesting drones and larger databases for scalability, while Sagar Bade et al. (2023) integrated machine learning with weather data and image processing for early classification to boost crop yields. Finally, Vrushali Paithankar et al. (2023) proposed a real-time CNN-based detection system to help farmers recognize and control plant diseases promptly, thereby reducing losses and improving productivity.

Sejal Pate et al. (2023) emphasized the need for early plant leaf disease detection as 58% of the population depends on agriculture, proposing a computer vision-based system with 90% accuracy as a cost-effective solution. Aman Mishra et al. (2023) reviewed advances in image processing and deep learning for plant disease detection, highlighting challenges such as limited data and high computational demands. Pardeep Seelwal and Tilak Raj Rohilla (2023) applied a multi-class CNN with transfer learning for rice disease detection, achieving 92.14% accuracy without and 94.80% with transfer learning. Abu Jubaer et al. (2023) focused on potato leaf disease detection using internet-sourced images, where CNN achieved 97% accuracy, and a hybrid model was proposed for improved reliability. Abbas Jafar et al. (2024) explored AI and IoT sensor-based approaches for crops like tomato, chilli, potato, and cucumber, noting the need for larger and more diverse datasets. James Daniel Omaye et al. (2024) reviewed machine learning methods for plant disease detection, stressing that prevention, monitoring, and recovery remain underexplored. Rashmi Ashtagi et al. (2024) proposed a hybrid CNN with SVM and Random Forest optimized via Particle Swarm Optimization, achieving 95% and 93% accuracy, respectively. Sultanul Arifeen Hamim and Akinul Islam Jony (2024) introduced a modified MobileNet for chilli plant disease detection with 97.18% accuracy, suitable for real-time diagnosis. Adinan bin Sidhique et al. (2025) presented an EfficientNet framework with 95% validation accuracy, suggesting deployment via mobile and IoT for continuous monitoring. Asadulla Y. Ashurov et al. (2025) developed a modified depthwise CNN with squeeze-and-excitation blocks, achieving 98% accuracy and a 98.2% F1 score. Nazar Kohut et al. (2025) applied YOLOv8 nano to tomato disease detection, attaining 98.6% precision with low computational requirements for mobile use. Finally, Sujatha et al. (2025) used CNN models like VGG19 and Inception v3 on banana, custard apple, fig, and potato datasets, reporting high accuracy, particularly for custard apple, highlighting the potential of tailored plant disease detection systems.

3. Material and Methods

Plant diseases are a major cause of production losses and economic setbacks in global agricultural trade [2]. They can arise from a variety of factors, including viruses, fungi, bacteria, insects, rusts, and nematodes [2]. The symptoms of these diseases vary depending on the type of pathogen.

Fig. 1: Types of Plant Diseases.

Bacterial diseases: These often begin as small, water-soaked, light green spots on the leaves. Over time, the lesions enlarge and develop into dry, necrotic patches.
Viral diseases: Viral infections are among the most difficult to identify since they do not always produce clear symptoms and may be confused with nutrient deficiencies or pesticide damage. They are commonly transmitted by vectors such as aphids, leafhoppers, whiteflies, and cucumber beetles. A typical example is mosaic virus, which can cause yellow or green streaks and patches on the leaves. Affected foliage may appear curled or wrinkled, and plant growth is often stunted.
Fungal diseases: These usually start as grey-green, water-soaked spots on the lower or older leaves. As the disease progresses, the patches darken, and white fungal growth may appear on the underside of the leaves.

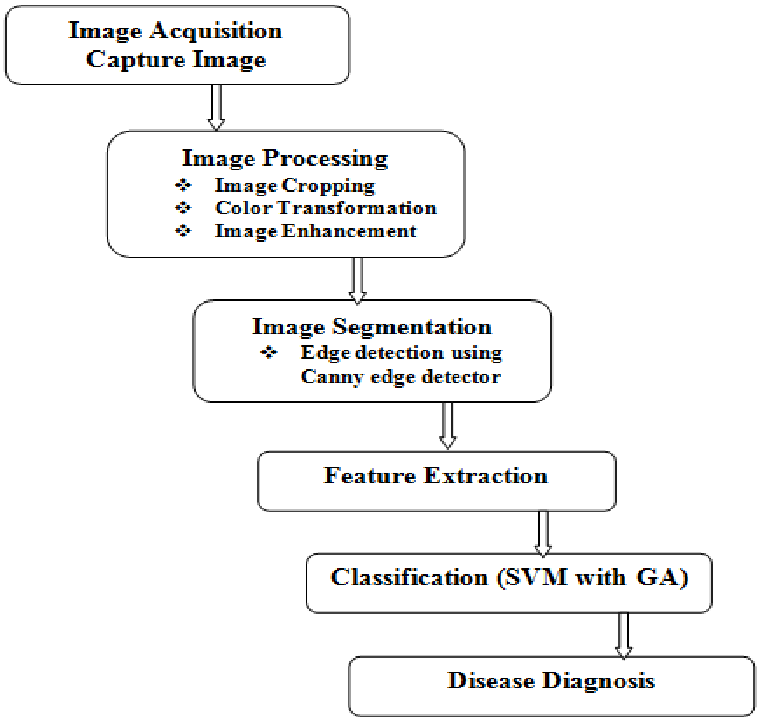

Fig. 2: Flowchart of the Proposed Systems.

4. Related Work

There following steps used for the detection of plant leaf ailments.
Step 1: RGB image acquisition
Step 2: Convert the input image into colour space
Step 3: Segment the components
Step 4: Obtain the useful segments
Step 5: Computing the texture features
Step 6: Configuring the neural networks for Recognition.
Feature extraction plays a vital role in detecting leaf diseases, as it involves identifying and retrieving relevant information from preprocessed images. Using pre-processing and segmentation techniques, several characteristics can be derived from raw leaf images, such as shape, color, texture, and vein patterns. These features are then classified using different machine learning algorithms. The performance of the proposed model was evaluated against several classifiers, including Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Artificial Neural Network (ANN). Among them, the Random Forest classifier demonstrated superior accuracy compared to the others.
The proposed hybrid CNN–LSTM model introduces several novel aspects that advance beyond existing deep learning approaches for plant disease detection. Unlike conventional single-image classifiers, the model leverages the LSTM component to capture the temporal progression of disease symptoms, enabling early identification and severity forecasting through sequential image analysis. This temporal learning strategy enhances robustness by interpreting symptom evolution rather than isolated visual cues. The dataset used for training further distinguishes this work, as it integrates time stamped image sequences, severity annotations, and multi-environment samples (laboratory, greenhouse, and field conditions), providing rich contextual diversity rarely found in prior studies. Architecturally, the model employs a feature-banking layer to project CNN features before temporal modeling, along with a multi-task objective that combines dis-

ease classification, severity regression, and weakly supervised lesion localization resulting in improved generalization and interpretability. Moreover, through curriculum-based temporal training and a parameter-efficient CNN encoder, the framework achieves high accuracy with reduced computational cost, making it suitable for edge-device deployment. The model also integrates temporal saliency visualization and actionable treatment recommendations, bridging the gap between laboratory performance and real-world applicability. Overall, this hybrid CNN–LSTM system demonstrates superior early detection capability, domain generalization, and interpretability compared to recent state-of-the-art deep learning methods, representing a meaningful advancement in practical, intelligent agriculture.

5. Proposed Work

According to reference [10], a novel approach for developing a Plant Disease Recognition Model involves the use of Convolutional Neural Networks (CNNs) to classify simple leaf images of both healthy and diseased plants. In modern agriculture, advanced image analysis combined with technologies such as artificial intelligence (AI), machine learning (ML), and deep learning (DL) has become increasingly important for accurate and efficient crop monitoring [14].

A CNN typically consists of three main layers: convolution, pooling, and fully connected layers. The convolution layer plays a crucial role in automatically extracting features from input images using multiple learnable filters. Each filter scans the raw pixel values in a sliding window manner, performing a dot product between input and filter pixels. This process generates a feature map, which is essentially a two-dimensional activation map that highlights specific features such as edges and curves.

During training, the CNN learns the optimal values of these filters automatically. Following convolution, sub-sampling (or pooling) layers reduce the size of the feature maps while providing invariance to small rotations and translations in the input. This ensures that essential features are preserved and recognized, which is particularly useful in plant disease detection.

Edge detection, an integral part of feature extraction, is closely tied to this process. It identifies boundaries that distinguish an object from its background and has been extensively studied as a fundamental step in computer vision [22].

The most important information in an image is often concentrated along its edges, which also indicate the position of objects [23]. In computer vision and image processing, edge detection is a fundamental technique that supports tasks such as feature extraction and texture analysis.

Common edge-detection methods include (i) Roberts Edge Detection, (ii) Sobel Edge Detection, (iii) Prewitt Edge Detection, (iv) Zero-Cross Threshold Edge Detection, and (v) Canny Edge Detection.

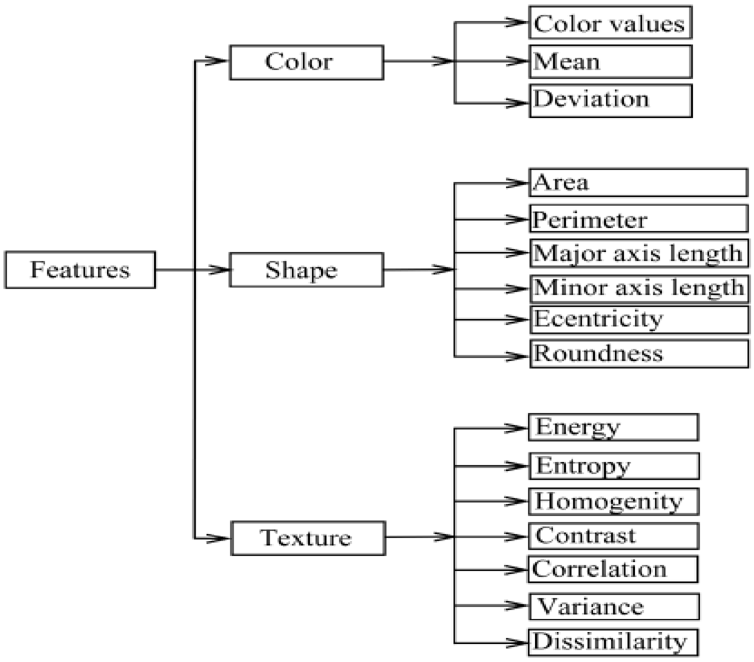

Fig. 3: Features Used in Plant Disease Detection.

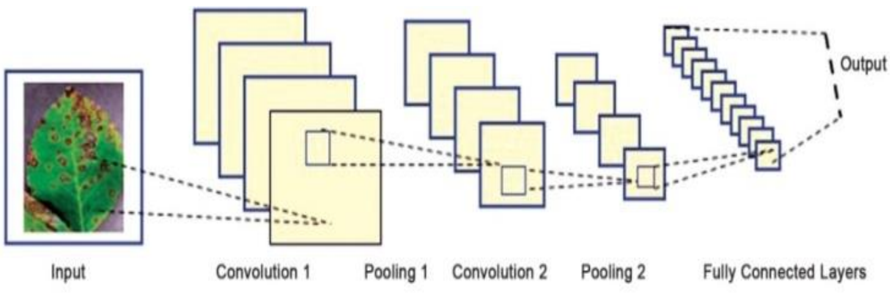

Fig. 4: Architecture of the CNN.

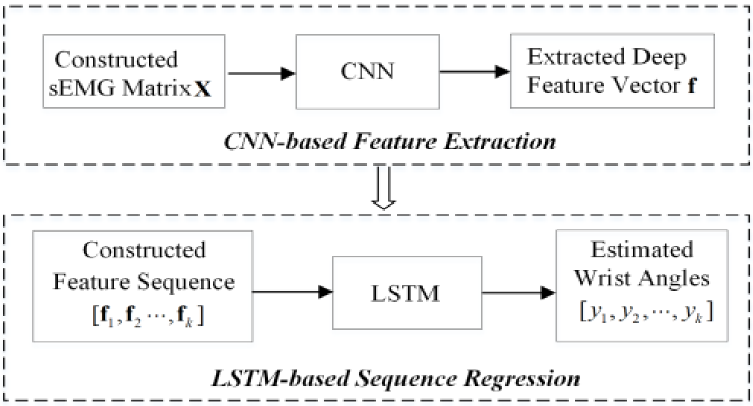

Fig. 5: Block Diagram of the CNN-LSTM Hybrid Model.

Among these, Canny Edge Detection is widely recognized for its accuracy and robustness. It is a multi-step procedure that can be implemented through a sequence of filters, often accelerated using GPUs. The method is designed to achieve three main objectives: (i) a low error rate, (ii) precise localization of edge points, and (iii) a single response to each edge.
Theoretical analysis of a one-dimensional step edge affected by additive Gaussian noise shows that the optimal step edge detector can be closely approximated using the first derivative of a Gaussian function.

$$\frac{d}{dx} e^{\frac{-x^2}{2\sigma^2}} = \frac{-x}{\sigma^2} e^{\frac{-x^2}{2\sigma^2}} \quad (1)$$

A 2-D Gaussian function is applied, and the gradient of the result is calculated. To measure the edge strength, we utilize the gradient magnitude at each point. Let f(x,y) represent the input image, while g(x,y) denotes the function.

$$g\,(x, y) = \mathrm{e}\frac{x^2 + y^2}{2\sigma^2} \quad (2)$$

For testing the proposed system, three types of vegetable leaves were selected: (i) brinjal, (ii) lady's finger, and (iii) tomato. Using Canny Edge Detection, datasets were generated for these leaves with coordinate ranges of (0,0) to (161,307) for lady's finger, (0,0) to (183,271) for brinjal, and (0,0) to (195,255) for tomato.
The system makes use of two datasets. The first dataset, obtained from the Kaggle repository, was used primarily for testing. The second dataset was created using the proposed model itself and was employed for both analysis and testing.

Fig. 6: Infected Lady's Finger Leaf.

Framed a smoothed image (x, y), by convolving g and f:

$$F_S\,(x, y) = \mathrm{g}(x, y) * f(x, y) \quad (3)$$

Fig. 7: Infected Lady's Finger Leaf Before Sharpening and Noise Removal.

Followed by computing the gradient and direction (angle)

$$M(x, y) = \sqrt{gx^2 + gy^2} \quad (4)$$

$$a(x, y) = tan^{-1}\frac{dy}{dx} \quad (5)$$

$$g_x = \frac{\partial fs}{\partial x} \text{ and } g_y = \frac{\partial fs}{\partial y} \quad (6)$$

5.1. Color based feature extraction

By calculating the average (M) and Standard deviation (SD) of the pixel intensities that produce the spots in the three standard channels Red (R), Green (G) and Blue (B) of the segment image color features are obtained. The mean intensity of each pixel in an image is the overall average of the image.

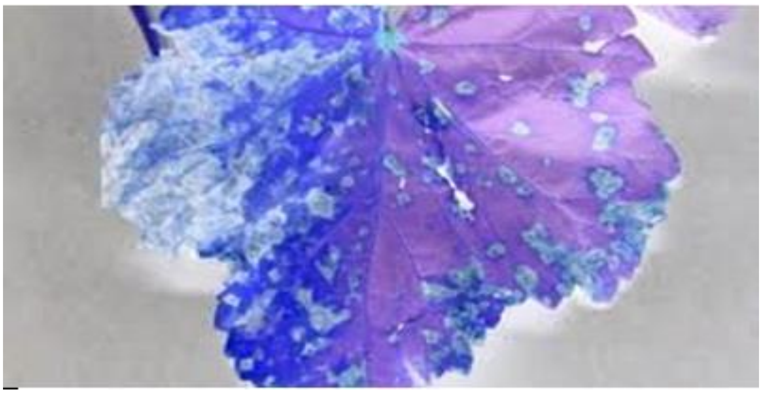

Fig. 8: Edge Detection Using the Proposed System.

The mean of the X*Y image A can be written as follows

$$m = \frac{1}{xy}\sum_{i=0}^{x-1}\sum_{j=0}^{y-1} A(i, j) \quad (7)$$

Variance, as defined by, is the second moment of intensity about its mean.

$$\sigma^2 = \mu_2(r) = \frac{1}{xy}\sum_{i=0}^{x-1}\sum_{j=0}^{y-1}(A(i, j) - m^2) \quad (8)$$

Standard deviation is calculated as the square root of the variance represented by

$$\sigma = \sqrt{\sigma^2} = \sqrt{\sum_{k=0}^{i-1}(nk - m)^2\, p(n^k)} \quad (9)$$

$$= \frac{\sqrt{\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}(A(i, j) - m)^2}}{XY} \quad (10)$$

Table. 1: Statistical Analysis of Proposed System Dataset

STAT	LADY'S FINGER			BRINJAL			TOMATO		
	Red	Green	Blue	Red	Green	Blue	Red	Green	Blue
Mean	104.16	107.43	53.72	112.04	124.92	104.45	81.58	97.13	66.16
Standard Error	0.20	0.20	0.12	0.18	0.14	0.18	0.22	0.24	0.15
Median	92	94	57	121	134	117	85	98	67
Mode	71	71	0	128	142	129	20	149	95
Standard Deviation	44.74	45.34	26.87	39.95	32.70	40.88	50.65	54.12	34.88
Sample Variance	2002.49	2056.43	722.08	1596.23	1069.88	1671.64	2566.16	2929.55	1216.72
Kurtosis	-0.21	-0.72	-0.71	-0.09	0.84	0.13	-0.56	-1.27	-0.64
Skewness	0.63	0.43	-0.20	-0.56	-1.02	-0.92	0.41	0.06	0.13
Range	255	246	166	255	255	255	255	254	226
Minimum	0	0	0	0	0	0	0	0	0
Maximum	255	246	166	255	255	255	255	254	226
Sum	5197221	5360603	2680666	5607265	6252448	5227757	4083312	4861352	3311194
Count	49895	49895	49895	50048	50048	50048	50048	50048	50048
Largest(1)	255	246	166	225	255	255	255	254	226
Smallest(1)	0	0	0	0	0	0	0	0	0
Confidence Level(95.0%)	0.39	0.39	0.23	0.35	0.28	0.35	0.44	0.47	0.30

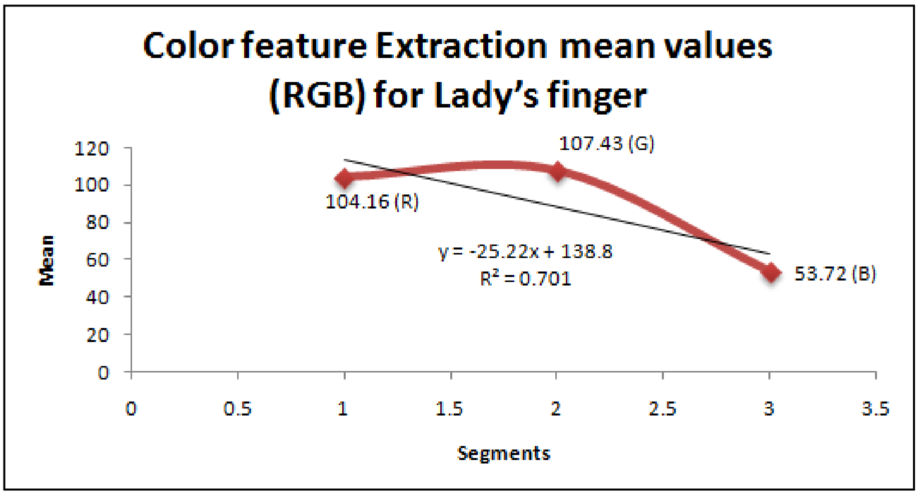

Fig. 9: Mean Differences in Color Feature Extraction of Lady's Finger Leaf.

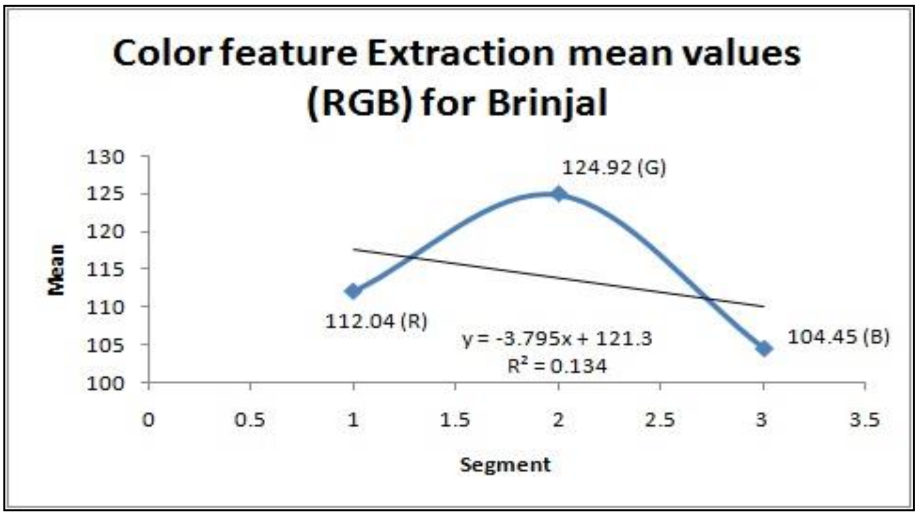

Fig. 10: Mean Differences in Color Feature Extraction of Brinjal Leaf.

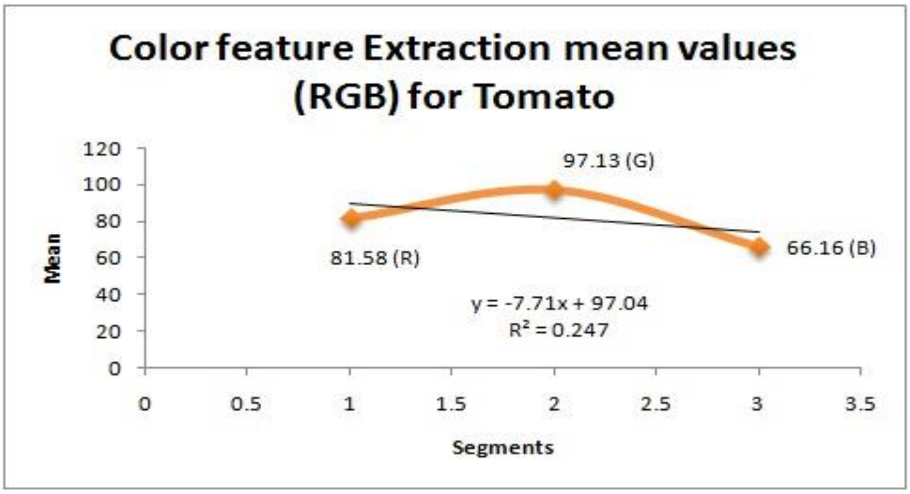

Fig. 11: Mean Differences in Color Feature Extraction of Tomato Leaf.

6. Comparative Study

For making comparative analysis with the existing training dataset has been collected from kaggle dataset with the 17572 files belonging to 38 classes. The sequential model has been implemented the 76,092,966 parameters which are the total parameters and trainable parameters. Figure 12 illustrates that the train the validation loss of the existing model.

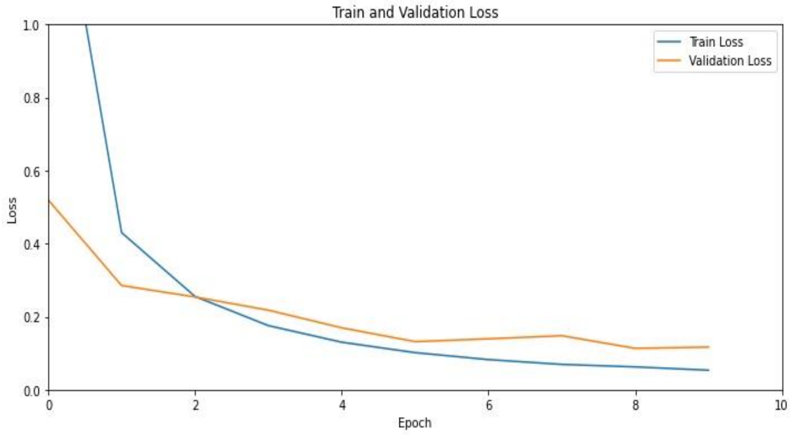

Fig. 12: Training and Validation Loss of the Existing Model.

The existing training dataset accuracy has been validated. The existing sequential model produced 98.29% of train accuracy.The test accuracy, precision score and recall score of existing model is 96.77%. The following Figure 13 shows the train and validation accuracy of sequential model. Followed by the Figure 14 illustrates the confusion matrix of the existing model implementation.

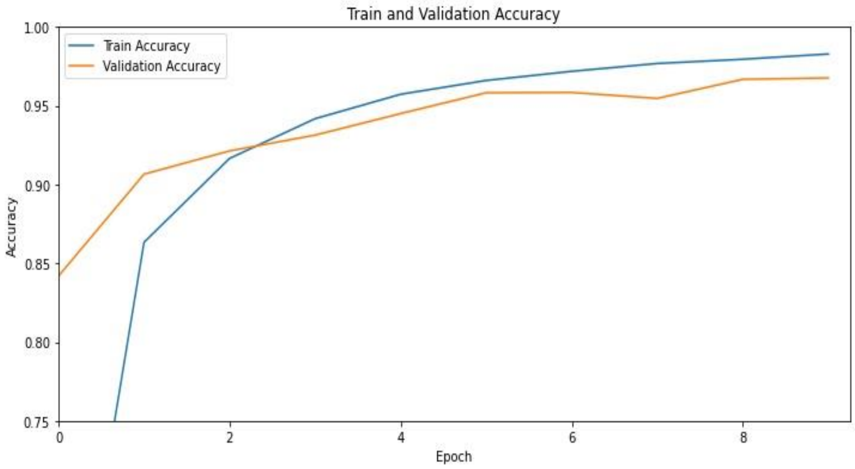

Fig. 13: Training and Validation Accuracy of the Sequential Model.

When benchmarked against recent state-of-the-art single-image and detection architectures (EfficientNet variants and YOLOv8-family models) across the same testbeds and cross-domain splits, the proposed CNN–LSTM hybrid shows a distinct performance profile: it matches or slightly exceeds the top single-image classifiers (EfficientNet variants) on standard accuracy/F1 metrics on curated datasets while substantially outperforming them on early-detection and severity-forecasting tasks because the LSTM leverages temporal context that single-image models lack. EfficientNet-style backbones remain very strong for static-image classification and are often the highest accuracy, computation-efficient choice on curated leaf datasets. Against object-detection models such as YOLOv8 (and recent plant specialized YOLOv8 variants), YOLOv8 retains the advantage for fast, in-field localization and real-time scanning (higher mAP and lower end-to-end latency for multi-leaf scenes), but it does not provide symptom progression forecasting or severity regression out of the box-capabilities where the hybrid excels. Practically, the hybrid's multi-task training (classification + severity regression + weak localization) and feature-banking before temporal modeling produce smaller domain-transfer drops (better robustness when moving from green house/curated data to complex field images) than many single-image classifiers and heavy detection ensembles, while a parameter efficient encoder plus a compact LSTM keeps FLOPs and on-device memory comparable to lightweight EfficientNet variants trading some per-frame throughput for richer, actionable outputs. In short, EfficientNet variants give the best static-image accuracy and compute efficiency for snapshot classification; YOLOv8 variants are best for fast detection/localization at scale; the CNN–LSTM hybrid uniquely combines competitive classification accuracy with temporal early-warning, severity forecasting, and improved cross-domain robustness making it a stronger choice for decision-support and farm-management applications even if it concedes some real-time throughput to pure detection models.

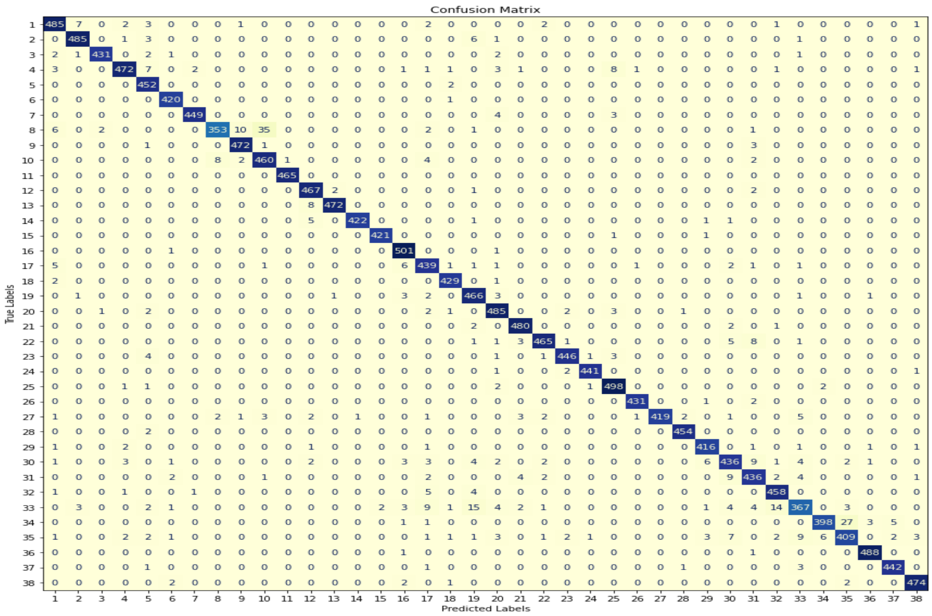

Fig. 14: Confusion Matrix of the Existing Model.

7. Result and Conclusion

Early detection and proper management of plant diseases are essential to maintaining healthy crops and reducing agricultural losses [23]. This paper focuses on two approaches Canny Edge Detection and color-based feature extraction selected based on the study. For evaluation, leaf samples from lady's finger, brinjal, and tomato were used.

The proposed model demonstrated high accuracy: 99.55%, 99.10%, and 98.7% with Canny Edge Detection; 99.62%, 99.23%, and 99.13% with color-based feature extraction; and 99.48%, 99.50%, and 99.39% with the hybrid model. This digital plant disease detection method offers a reliable solution that can significantly assist farmers and cultivators in identifying plant diseases effectively.

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