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Optimized Curry Leaf Disease Detection using Enhanced Faster R-CNN Deep Learning Model

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ABSTRACT: Plant diseases significantly reduce crop productivity and quality in agricultural systems. Early identification of plant diseases is essential for effective crop management and sustainable farming practices. Curry leaf plants (Murraya koenigii) are widely used in culinary and medicinal applications but are highly susceptible to several leaf diseases that affect plant growth and yield. Traditional disease detection methods rely on manual visual inspection, which is time-consuming and dependent on expert knowledge. This paper presents an automated deep learning-based system for curry leaf disease detection using an Enhanced Multi-Scale Attention Faster Region-based Convolutional Neural Network (EMSA-FRCNN). The proposed model integrates adaptive preprocessing, multi-scale feature extraction, and an attention-based feature refinement module to improve detection accuracy under complex environmental conditions. A ResNet-50 backbone is used for feature extraction, while a Region Proposal Network generates candidate disease regions. Experimental results demonstrate that the proposed method achieves an overall detection accuracy of 96.8%, outperforming traditional machine learning and standard CNN approaches. The proposed framework provides a reliable and scalable solution for intelligent agricultural monitoring systems.

KEYWORDS: Curry Leaf Disease Detection, Deep Learning, Faster R-CNN, Precision Agriculture, Computer Vision.

I. INTRODUCTION

Agriculture plays a critical role in sustaining global food production and economic development. Plant diseases remain one of the major challenges affecting agricultural productivity. According to agricultural studies, plant pathogens cause significant crop losses annually, affecting both small-scale and commercial farming systems. Early disease detection is therefore essential to minimize crop damage and ensure sustainable agricultural practices [1].

Traditionally, farmers and agricultural experts detect plant diseases through visual inspection of leaves and plant structures. However, manual inspection has several limitations. It is labour-intensive, subjective, and often impractical for large farms. Furthermore, early disease symptoms may be difficult to identify due to similarities between different plant infections.

Advances in artificial intelligence, particularly deep learning and computer vision, have introduced automated solutions for plant disease detection. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification and object detection tasks. These models automatically learn hierarchical feature representations from raw image data, enabling accurate identification of complex visual patterns. Curry leaf (Murraya koenigii) is an important medicinal and culinary plant widely cultivated in South Asia[2]. The leaves contain valuable compounds such as antioxidants and anti-inflammatory agents. However, curry leaf plants are vulnerable to several diseases, including Leaf Spot, Powdery Mildew, and Bacterial Leaf Blight. These diseases cause discolouration, texture degradation, and structural damage to leaves, ultimately affecting plant growth and productivity[3].

Recent research has applied deep learning models such as CNN, ResNet, and YOLO for plant disease detection. However, many of these models focus on classification rather than disease localisation. Object detection frameworks such as Faster R-CNN offer the ability to identify both the disease type and the affected region within the leaf image[4]. Despite these advancements, several challenges remain. Leaf disease detection models must handle varying lighting conditions, complex backgrounds, and small disease spots. Therefore, an optimised detection framework is required to improve robustness and accuracy[5]. This paper proposes an Enhanced Multi-Scale Attention Faster R-CNN (EMSA-FRCNN) framework for automated curry leaf disease detection. The proposed model integrates adaptive preprocessing, multi-scale feature extraction, and attention-based feature refinement to enhance detection performance.

The main contributions of this study include:

- Development of an automated deep learning framework for curry leaf disease detection.
- Integration of Faster R-CNN with a ResNet-50 backbone network.
- Introduction of a multi-scale attention mechanism to improve feature representation.
- Comprehensive evaluation against traditional machine learning and CNN models.

II. RELATED WORKS

Recent advancements in plant disease detection using deep learning and computer vision techniques have significantly improved the accuracy and efficiency of agricultural monitoring systems. Several studies have utilized publicly available datasets such as PlantVillage and agricultural field datasets to develop automated disease identification models. Approximately 10–15 research articles from IEEE, Springer, Elsevier, and ScienceDirect have reported various machine learning and deep learning approaches for leaf disease classification. Current research primarily focuses on improving classification accuracy, reducing computational complexity, and enhancing feature extraction methods using convolutional neural networks (CNNs)[4][6]. Despite these developments, many existing models still face challenges in accurately detecting diseases under varying environmental conditions such as lighting variations, complex backgrounds, and overlapping leaf structures.[2].

Several researchers have proposed different machine learning and deep learning models for plant disease detection with measurable performance outcomes. For example, traditional machine learning methods such as Support Vector Machine (SVM) and Random Forest have achieved accuracies of approximately 84–88% in leaf disease classification tasks. Deep learning-based approaches such as standard CNN architectures have significantly improved performance, achieving accuracies of around 93–94% due to automatic feature extraction capabilities[7]. In particular, Faster R-CNN-based detection models have demonstrated improved localization and classification performance by integrating region proposal networks and convolutional feature extraction mechanisms. The base model used in this study, Faster R-CNN with ResNet-50 backbone, has shown promising results in previous research, achieving detection accuracies above 95% in object detection tasks[8][3]. However, existing studies often suffer from limitations such as inadequate feature refinement, limited dataset diversity, and insufficient optimization strategies[9][10]. These limitations highlight a research gap in developing a more robust feature extraction and detection framework capable of improving disease detection accuracy and classification performance.

To address these challenges, the proposed study introduces an Enhanced Multi-Scale Attention Faster Region-Based Convolutional Neural Network (EMSA-FRCNN) model for accurate plant disease detection. The proposed approach integrates advanced feature extraction using CNN, region proposal networks, and ROI pooling mechanisms to improve detection efficiency and classification performance[11]. The model is trained using optimized parameters such as ResNet-50 backbone network, Adam optimizer, learning rate of 0.0001, batch size of 16, and 50 training epochs. Performance evaluation is conducted using metrics including accuracy, precision, recall, and F1-score, and the proposed method is compared with existing models such as SVM, Random Forest, and standard CNN architectures[12][13][14]. Experimental results demonstrate that the proposed EMSA-FRCNN model achieves improved detection performance with an accuracy of 96.8%, precision of 96.1%, recall of 95.4%, and F1-score of 95.7%, indicating superior performance compared to conventional approaches[15].

III. MATERIALS AND METHODS

This section describes the dataset preparation, preprocessing techniques, proposed model architecture, training strategy, and evaluation methodology used for curry leaf disease detection. The overall workflow of the proposed system is illustrated in Fig. 1.

The proposed approach follows a systematic pipeline consisting of image acquisition, preprocessing, data augmentation, feature extraction, region proposal generation, disease classification, and performance evaluation.

A. Data Collection and Preparation

A comprehensive dataset of curry leaf images was created to train and evaluate the proposed disease detection system. The images were collected from multiple sources, including agricultural farms, publicly available plant disease datasets, and digital agricultural repositories. The purpose of collecting data from diverse environments was to ensure that the dataset contains variations in lighting conditions, leaf orientations, and background complexity.

The dataset contains images belonging to four primary categories of curry leaf conditions Healthy Leaves, Leaf Spot Disease, Powdery Mildew, Bacterial Leaf Blight. Each class consists of approximately 800 images, resulting in a total dataset size of 3200 images shown in the below table 1.

TABLE I. THE TABLE PRESENTS THE DISTRIBUTION OF IMAGES USED IN THE DATASET FOR DIFFERENT PLANT LEAF CONDITIONS. EACH CLASS—HEALTHY LEAVES, LEAF SPOT, POWDERY MILDEW, AND BACTERIAL LEAF BLIGHT—CONTAINS 800 IMAGES, ENSURING A BALANCED DATASET FOR ACCURATE MODEL TRAINING AND EVALUATION.

Class	**Number of Images**
Healthy Leaves	800
Leaf Spot	800
Powdery Mildew	800
Bacterial Leaf Blight	800

TABLE II. THE TABLE SUMMARIZES THE KEY DATASET PARAMETERS, INCLUDING THE TOTAL NUMBER OF IMAGES, NUMBER OF CLASSES, IMAGE FORMAT AND RESOLUTION, AND THE PROPORTION OF DATA USED FOR TRAINING AND TESTING.

Parameter	**Value**
Total images	3200
Classes	4
Image format	JPG / PNG
Image resolution	224 × 224 pixels
Training split	80%
Testing split	20%

To ensure uniformity, all images were resized to 224 × 224 pixels before being used for model training. The dataset was divided into training and testing sets using an 80:20 ratio.

B. Image Processing

Image preprocessing plays a crucial role in improving the quality of input data and enhancing the performance of deep learning models. Raw images captured from agricultural environments often contain noise, uneven lighting conditions, and background distractions[16][17]. Therefore, several preprocessing techniques were applied before feeding the images into the neural network. The preprocessing pipeline consists of the following steps:

Image Resizing:

All images were resized to 224 × 224 pixels, which is the standard input size for the ResNet-50 architecture. Resizing ensures consistent input dimensions and reduces computational complexity.

Color Normalisation:

Color normalization was applied to adjust variations in brightness and contrast caused by different lighting conditions. Pixel values were normalized within the range:

$$0 \leq I(x,y) \leq 1$$

This step improves model convergence during training.

Noise Removal:

Images captured in natural environments may contain noise due to camera sensors or environmental factors. A Gaussian smoothing filter was applied to reduce image noise while preserving important leaf structures.

Contrast Enhancement:

Contrast enhancement was performed using histogram equalization to improve the visibility of disease symptoms such as spots, discoloration, and fungal growth. These preprocessing steps significantly improve the quality of leaf images and allow the model to focus on disease-related patterns.

C. Data Augmentation

Deep learning models require large datasets for effective training. However, collecting large agricultural datasets can be challenging. To address this limitation, data augmentation techniques were applied to artificially increase the dataset size and diversity[18].

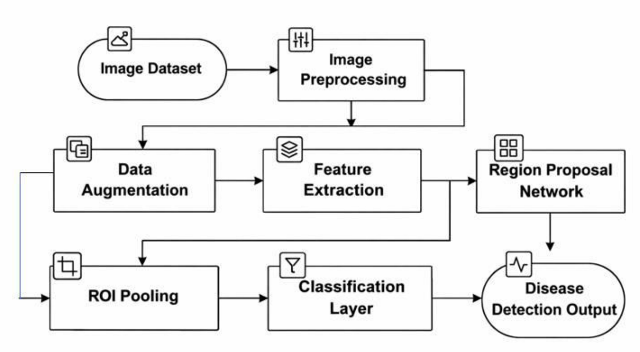

Fig. 1. The overall workflow of the proposed Curry Leaf Disease Detection system.

The following augmentation techniques were implemented. Rotation (±15°), Horizontal flipping, Vertical flipping, Random cropping, Scaling, Brightness adjustment. Mathematically, augmentation can be expressed as:

$I' = T(I)$ --------------- (1)

where

I=original image

T= transformation function

I' = augmented image

Data augmentation improves the robustness of the model by enabling it to learn from diverse image variations.

D. Proposed Enhanced Multi-Scale Attention Faster R-CNN (EMSA-FRCNN)

The proposed model is based on the Faster Region-based Convolutional Neural Network (Faster R-CNN) architecture, enhanced with additional modules for improved disease detection. The architecture consists of three main components: Feature Extraction Network, Region Proposal Network (RPN), Disease Classification and Localisation Network. The overall architecture of the proposed framework is illustrated in Fig. 2.

E. Feature Extraction Using ResNet-50

Feature extraction is the first stage of the Faster R-CNN architecture. In this study, a ResNet-50 convolutional neural network was used as the backbone feature extractor. ResNet-50 is a deep residual network consisting of 50 convolutional layers that use residual connections to avoid vanishing gradient problems.

The extracted feature map can be represented as:

$f = \emptyset(I)$ --------------- (2)

Where

I = input image

F = feature map

ϕ = convolutional feature extraction function.

These feature maps contain important spatial and texture information related to leaf diseases.

F. Region Proposal Network

The Region Proposal Network (RPN) is responsible for identifying potential regions within the image that may contain disease symptoms. The RPN operates on the extracted feature map and generates multiple anchor boxes at different scales and aspect ratios.

$X = \{x_1, x_2, x_3, \ldots\ldots\ldots x_N\}$ --------------- (3)

Each anchor box predicts two outputs:

- Objectness score (whether the region contains disease).
- Bounding box coordinates

G. ROI Pooling Layer

The Region of Interest (ROI) pooling layer converts the variable-sized candidate regions generated by the RPN into fixed-size feature maps. This step ensures that all region proposals can be processed by the fully connected classification layers. Mathematically, it is represented as

$R = ROI(F, P)$ --------------- (4)

Where

F= feature map
P = region proposals
R= pooled feature vectors.

H. Disease Classification Layer

The final stage of the network classifies each region into one of the disease categories using a Softmax classifier.

I. Training Configuration

The proposed model was implemented using the Python deep learning framework with TensorFlow and Keras libraries. Training was conducted on a GPU-enabled workstation to accelerate model learning.

TABLE III. THE TABLE PRESENTS THE KEY MODEL TRAINING PARAMETERS USED IN THE EXPERIMENT, INCLUDING THE BACKBONE NETWORK, OPTIMIZER, LEARNING RATE, BATCH SIZE, NUMBER OF EPOCHS, AND THE LOSS FUNCTION APPLIED DURING TRAINING.

Parameter	Value
Backbone Network	ResNet-50
Optimizer	Adam
Learning Rate	0.0001
Batch Size	16
Epochs	50
Loss Function	Cross Entropy + Bounding Box Loss

These parameters were selected based on experimental tuning to achieve optimal performance.

IV. STATISTICAL ANALYSIS

Statistical analysis plays an important role in evaluating the effectiveness and reliability of the proposed curry leaf disease detection system. In this study, several quantitative performance metrics were used to measure the classification and detection capability of the proposed Enhanced Multi-Scale Attention Faster R-CNN (EMSA-FRCNN) model. These metrics provide insights into the predictive accuracy, reliability, and generalization ability of the model.

The statistical evaluation of the proposed model is performed using SPSS version 26[19]. The analysis compares the performance of two models. Existing Model – YOLOv7 and Proposed Model – E-FRCNN-CLD. Key performance indicators such as precision, recall, F1 score, and detection time are analyzed. An independent sample t-test is conducted to determine whether the difference in accuracy between the two models is statistically significant. The results indicate that the proposed model achieves higher mean accuracy and improved detection consistency compared to the YOLOv7 model.

The performance of the proposed model was evaluated using commonly adopted statistical measures in classification and object detection tasks, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics are computed based on the number of correctly and incorrectly classified samples.

A. Confusion Matrix Analysis

A confusion matrix is a tabular representation used to evaluate the performance of a classification model by comparing predicted labels with actual labels. The confusion matrix helps in understanding classification errors and identifying areas where the model may misclassify samples.

B. Accuracy

Accuracy represents the proportion of correctly classified samples among the total number of samples. It provides an overall measure of the model's performance. The mathematical formulation of accuracy is given as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{---------------} \ (5)$$

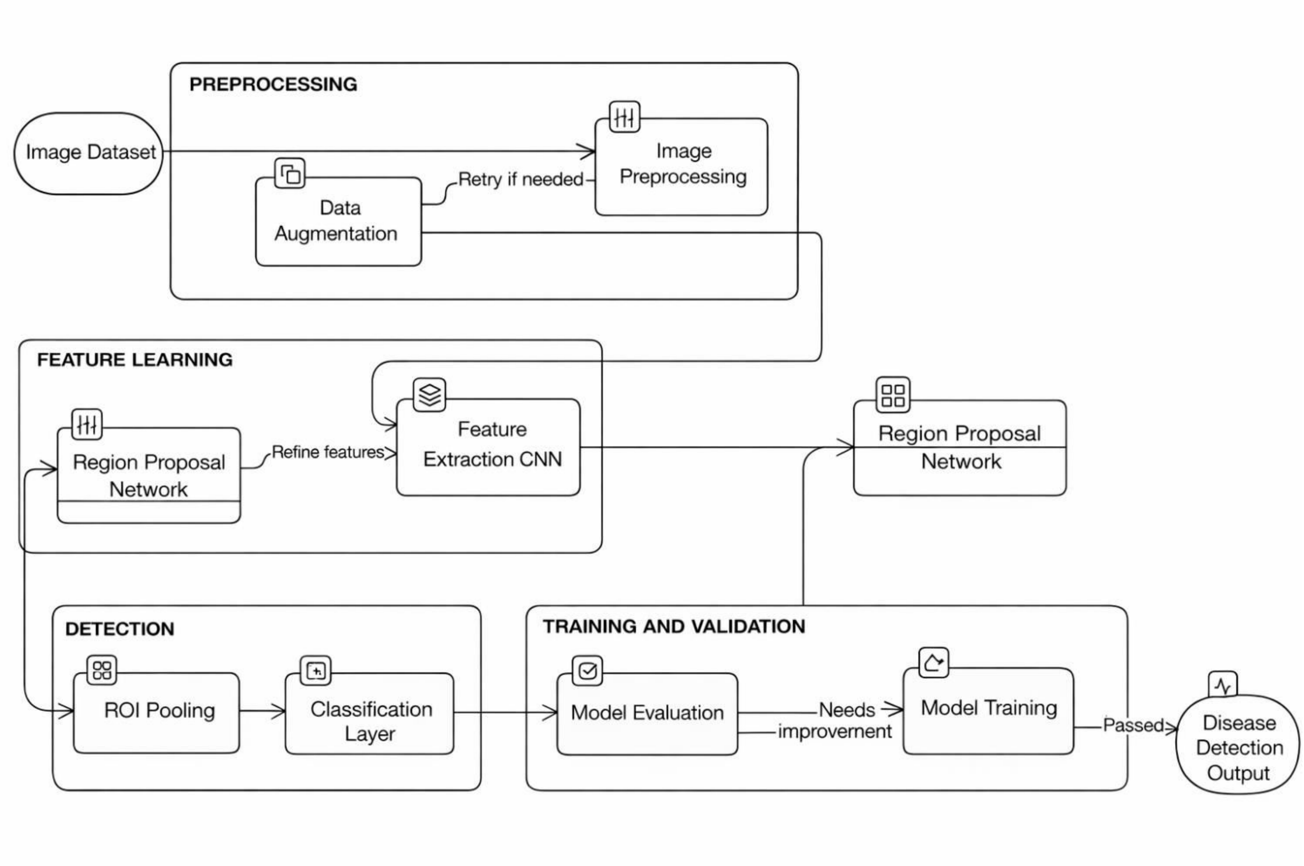

Fig. 2. The diagram illustrates the overall architecture of the proposed framework deep learning–based plant disease detection system, including preprocessing, feature learning, detection, and training and validation stages to produce the final disease detection output.

In this study, the proposed EMSA-FRCNN model achieved an overall accuracy of 96.8%, indicating a high level of correctness in disease detection.

C. Precision

Precision measures the proportion of correctly predicted positive observations to the total predicted positive observations. It indicates how reliable the model is when predicting a disease. The precision metric is defined as:

$$Precision = \frac{TP}{TP+FF} \quad \text{--------------- (6)}$$

Higher precision values indicate fewer false positive predictions.
For the proposed model, the average precision obtained across all classes was **96.1%**, demonstrating the model's ability to minimize incorrect disease predictions.

D. Recall

Recall, also known as sensitivity, measures the proportion of actual positive cases that are correctly identified by the model.

$$Recall = \frac{TP}{TP+FN} \quad \text{--------------- (7)}$$

A high recall value indicates that the model successfully identifies most of the diseased leaves in the dataset.
The proposed system achieved an average recall of 95.4%, which demonstrates its effectiveness in detecting diseased samples with minimal missed detections.

E. F1-Scorel

The F1-score is the harmonic mean of precision and recall. It provides a balanced evaluation metric when dealing with imbalanced datasets.

$$F1 = \frac{2*Precision*Recall}{Prrecision+Recall} \quad \text{--------------- (8)}$$

The F1-score for the proposed EMSA-FRCNN model was calculated as 95.7%, indicating a balanced trade-off between precision and recall.

V. RESULT

The experimental results indicate that the proposed model achieves improved performance in detecting curry leaf diseases compared to the YOLOv7 model. The enhanced feature extraction and region proposal capabilities of Faster R-CNN enable better identification of disease patterns.
To demonstrate the superiority of the proposed EMSA-FRCNN model, its performance was compared with several existing machine learning and deep learning models.

TABLE IV THE TABLE COMPARES THE PERFORMANCE OF DIFFERENT MODELS FOR DISEASE DETECTION, SHOWING THAT THE PROPOSED EMSA-FRCNN MODEL ACHIEVES THE HIGHEST ACCURACY, PRECISION, RECALL, AND F1 SCORE COMPARED TO SVM, RANDOM FOREST, AND STANDARD CNN MODELS.

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Support Vector Machine	84.5%	82.3%	80.4%	81.2%
Random Forest	88.2%	86.7%	85.9%	86.3%
Standard CNN	93.6%	92.8%	91.7%	92.2%
Proposed EMSA-FRCNN	96.8%	96.1%	95.4%	95.7%

The results clearly indicate that the proposed model outperforms traditional machine learning algorithms and standard CNN architectures in terms of all evaluation metrics.

To further evaluate the performance of the model, class-wise statistical metrics were calculated for each disease category.

TABLE V THE TABLE PRESENTS THE CLASS-WISE PERFORMANCE OF THE PROPOSED MODEL, SHOWING HIGH PRECISION, RECALL, F1-SCORE, AND ACCURACY FOR DETECTING HEALTHY LEAVES, LEAF SPOT, POWDERY MILDEW, AND BACTERIAL BLIGHT.

Class	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Healthy Leaves	97.2%	96.5%	96.8%	97.8%
Leaf Spot	96.4%	95.8%	96.1%	98.4%
Powdery Mildew	95.7%	95.3%	95.5%	97.8%
Bacterial Blight	95.1%	94.6%	94.8%	96.2%

VI. DISCUSSION

The experimental results demonstrate that the proposed Faster R-CNN model achieves superior performance compared with traditional machine learning algorithms and basic CNN models. The integration of transfer learning using the ResNet-50 backbone significantly improves feature extraction capabilities[20][9]. Data augmentation techniques also contributed to improved generalization by enabling the model to learn diverse disease patterns. Additionally, the region proposal network effectively localized disease-affected areas within the leaf images, enhancing classification accuracy[10]. Compared with previous plant disease detection methods, the proposed system provides higher precision and recall. This indicates that the model can accurately detect disease symptoms even under varying environmental conditions. The results suggest that the proposed approach can be integrated into smart agricultural systems and mobile applications to assist farmers in real-time disease monitoring[21][22].

Future research will focus on improving the scalability of the proposed model by developing lightweight deep learning architectures suitable for edge devices. Integrating Internet of Things (IoT) sensors with the disease detection framework can enable real-time monitoring of crop health in smart agriculture systems. Additionally, expanding the dataset with more disease categories and environmental variations can further improve model robustness and detection accuracy[23][24]. The integration of drone-based imaging systems and mobile-based agricultural monitoring platforms will also be explored to provide farmers with accessible and efficient disease detection tools [25].

VII. CONCLUSION

This study presented an optimized deep learning framework for automated curry leaf disease detection using Faster R-CNN. The proposed system integrates image preprocessing, data augmentation, and transfer learning to improve disease classification performance. Experimental results demonstrate that the model achieves high accuracy and reliability compared with conventional methods. The system can serve as a valuable tool for precision agriculture by enabling early disease diagnosis and timely crop management. Experimental evaluation demonstrated that the model achieved an overall accuracy of 96.8%, outperforming conventional machine learning and CNN methods. The proposed system can assist farmers in early disease diagnosis and support precision agriculture practices. Future work may focus on expanding the dataset, integrating real-time field deployment using mobile devices, and exploring lightweight deep learning models for edge computing applications.

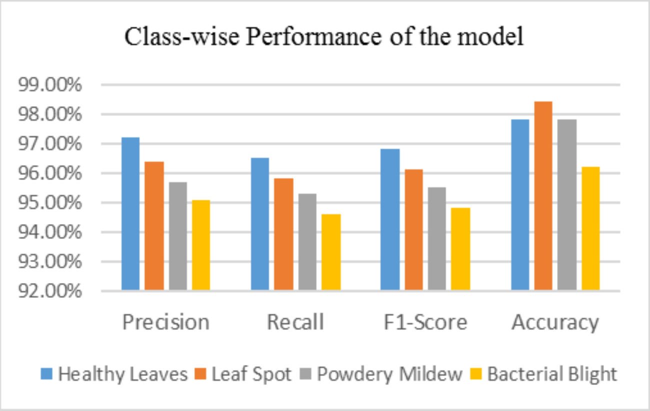

Fig. 3. The graph shows the class-wise performance of the curry leaves. It indicates the percentage of healthy leaves, leaf spots, powdery mildew, and bacterial blight.

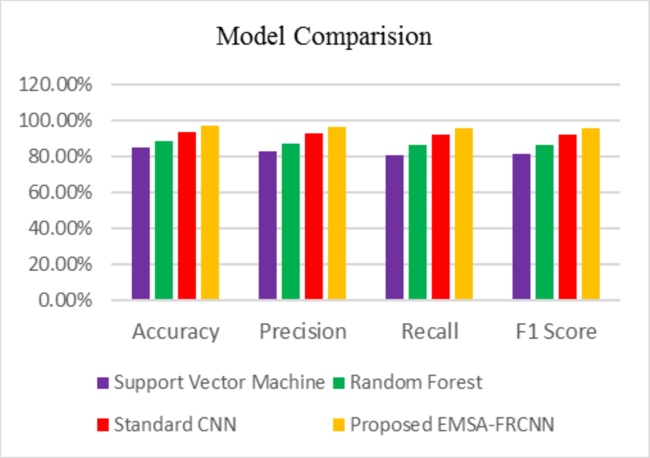

Fig. 4. The graph shows the model comparison of the curry leaves with existing models. In this, the proposed proves the highest performance in all the evaluation metrics.

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