Deep Learning Approaches for Efficient Detection and Classification of Plant Diseases

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Abstract. *Ensuring the prevention and management of plant diseases is crucial for achieving a successful plant yield. The study enhanced the accuracy of plant leaf disease detection by utilizing advanced techniques such as "single shot multi-box detectors," "faster region-based convolutional neural networks," and "You only look once-X." These techniques incorporate effective attention mechanisms, including the convolutional block attention module, squeeze and excitation networks, and efficient channel attention. The implementation of diverse attention approaches effectively highlighted significant attributes while minimizing the influence of unimportant ones, hence enhancing the accuracy of the models and enabling real-time execution. After evaluating the optimal models from the three types, it was determined that the Faster (R-CNN) model had a lower precision value. On the other hand, You Only Look Once-X and SSD with various attention techniques had the highest precision and required the fewest parameters. Additionally, these models demonstrated the best real-time performance. This study not only offered useful insights into the detection of plant leaf diseases, but also provided insights into plant illnesses and symptoms in automated agricultural production.*

Keywords:- Classification algorithms, Feature extraction, deep learning, Supervised learning, Plant disease detection, attention model.

Introduction

Preventing and controlling crop diseases is crucial for producing safe and healthy vegetables, minimizing losses, and reducing the use of pesticides in the production of crops [1]. Thus, early detection & prevention of diseases are crucial. Plant plants can be affected by various diseases, such as powdery mildew, brown blotch, and anthracnose, which can significantly impact the yield and quality of the fruit. Traditional methods of detecting plant diseases rely on the experience of the growers or the guidance of experts, which can be slow, inefficient, and lack real-time performance. Images of plant leaves are used to detect, identify, and provide guidance about diseases infected with plant leaves [2] because disease- infected plant leaves often have visible spots.

Plant leaf disease detection is crucial for several reasons. Firstly, it allows growers to monitor the health of their plantvines and take appropriate actions to prevent or manage diseases effectively. Early detection enables timely interventions, minimizing potential damage and crop losses. Different plant leaf diseases require specific treatments, and accurate identification helps growers implement targeted control measures.

This optimizes the use of pesticides, reduces environmental impact, and ensures effective disease management.

Plant leaf diseases can significantly impact the yield and quality of plantvine production. Some diseases cause defoliation, reducing the vine's ability to photosynthesize and produce energy, leading to decreased fruit quality, delayed ripening, and reduced yield. Early disease detection enables growers to protect the crop and implement measures to minimize yield losses. Early identification of plant leaf diseases is essential for preventing their spread within vineyards. Prompt isolation and treatment of infected vines help prevent diseases from affecting healthy plants. Additionally, preventive measures such as pruning, canopy management, and cultural practices can be implemented to reduce the likelihood of disease occurrence and spread. Economically, plantvines are valuable crops, and detecting diseases in plant leaves allows growers to make informed decisions on disease management, optimizing resource utilization, and reducing unnecessary costs. This helps preserve the economic viability of vineyards and sustain profitability in plant production.

Efficient disease detection and management practices also contribute to sustainable agriculture. Early identification minimizes the use of broad-spectrum pesticides, reducing their negative impact on the environment and non-target organisms. Targeted treatments based on accurate disease detection help reduce chemical inputs, promote ecological balance, and support sustainable cultivation practices for plantvines. In summary, plant leaf disease detection is vital for crop health monitoring, disease management, yield protection, disease prevention, economic considerations, and sustainable agriculture. Early detection allows for timely interventions, optimization of disease control measures, minimization of crop losses, and the long-term sustainability of plantvine production.

Due to the rapid development of artificial intelligence technologies, a wide variety of vision approaches are utilized in the processing of photos for various crop diseases [3][4][5]. Research into classifying agricultural diseases uses a wide range of approaches, including "genetic algorithms" [6], "sup- port vector machines" [7],"K-means clustering" [8], "ensemble learning" [9], "Bayesian classification" [10], "radial basis functions" [11], & "filter segmentation" techniques [12]. Unfortunately, conventional approaches to crop disease classification and identification rely on labour-intensive, environment- dependent manual feature selection. In particular, the development of deep learning's Convolutional Neural Network (CNN) has led to vast improvements in the field of autonomous detection and identification of agricultural diseases.

An object detection system that uses a convolutional neural network (CNN) has made great strides recently. Several applications make use of this technique, including recognition of faces [13], navigation [14], detection of road obstacles [15], detection of pedestrians, abnormal activity recognition [16], monitoring of physical activity [17],[18] detection of fruits, and detection of weeds [19]. Despite complex backdrops, crop leaf diseases can be detected using object detection algorithms due to CNN's ability to extract high-dimensional properties from object images.

As a result, scientists in China and others have studied object detection algorithms to develop models for detecting crop diseases. For instance, some authors have applied various models for object detection to the tomato disease dataset, including the Faster(R-CNN), and the Single Shot Multibox Detector. Faster (R-CNN) as well as VGG16 produced the best disease detection results. Dynamic identification of plant leaf illnesses was accomplished by using Faster (R-CNN) on time-series images of plant leaves. Using an enhanced Faster (R-CNN) model, the authors of [20] detected diseases in bitter gourd leaves with excellent results. Using an in-house dataset, the authors of [21] trained the SSD model to identify agricultural diseases with an overall accuracy of 83.90%. An enhanced model based on MobileNetv2 & YOLOv3 was proposed by the authors [22], which allowed for the early detection of grey speck disease in tomatoes. This refined model benefits from a number of desirable characteristics, including a low memory size, outstanding detection accuracy, and lightning-fast identification.

Rest of the paper is organized as follow: section 2 describes various research work done previously in the field of plant disease detection, section 3 shows the proposed method with different attention mechanisms, section 4 evaluates results of proposed method on different parameters, section 5 concludes the work followed by references used in this study.

Related Work

In this study, the author has analyzed the literature on various plant leaf disease detections and classifications, as well as the models/techniques that have been used.

According to [23], DL-based solutions for real-time insect detection and identification in the soybean crop have been proposed. The performances of various transfer learning (TL) models were investigated to determine the feasibility and reliability of the pro- posed approach for determining the insect's identification and detection accuracy. The proposed approach achieved 98.75%, 97%, and 97% accuracy using YoloV5, InceptionV3, and CNN, respectively. Among these, the YoloV5 algorithm performs quite well in the solution and can run at 53 fps, making it suitable for real-time detection. Furthermore, a dataset of crop insects was collected and labeled by mixing images taken with various devices. The proposed study reduced the workload of the producer, was considerably simpler, and produced better results. The authors of [24] have proposed a system that uses DL approaches to classify and detect plant leaf diseases. They collected the images from the PlantVillage dataset website. They used the CNN to classify plant leaf diseases in the suggested method. There were 15 classes, including 12 classes for diseases of various plants that were found, such as bacteria, fungi, and so on, and three classes for healthy leaves. As a result, they achieved high accuracy in both training and testing, with an accuracy of 98.29% in training and 98.029% in testing for all data sets used.

In the study of [25], an effective method for recognizing and identifying rice plant disease based on the size, shape, and color of lesions in a leaf image has been presented. The suggested model uses Otsu's global threshold technique to perform image binarization to remove image background noise. To detect the three rice diseases, the proposed technique based on a fully connected CNN was trained using 4000 image samples of each diseased leaf and 4000 image samples of healthy rice leaves. The results revealed that the proposed fully connected CNN approach was fast and effective, with an accuracy of 99.7% on the dataset. This accuracy far exceeded that of the existing plant disease detection and classification methods. The authors of [26] have presented a model based on CNN to identify and classify tomato leaf disease using a public dataset and complement it with images taken on the country's farms. To avoid overfitting, generative adversarial networks were used to generate samples that were similar to the training data. The results reveal that the proposed model performed well in the detection and classification of diseases in tomato leaves, with accuracy greater than 99% in both the training and test datasets.

The authors of [27] have used the dataset "PlantVillage" to depict four bacterial infections, two viral diseases, two mold diseases, and one mite-related ailment. Images of unaffected leaves were also shown for a total of 12 crop species. For the development of prediction models, ML approaches such as SVMs, grey-level co-occurrence matrices (GLCMs), and CNNs were used. AI for classification has evolved alongside the development of the backpropagation of ANNs. Based on the real-time leaf images gathered, a KMC operation was also performed to detect diseases. Finally, the proposed approach achieved an overall accuracy of 99% and 98% for rice trees and apples, respectively, and 96%, 94%, 95%, and 97% for tomato trees. Multi-class classification problems, such as the one in this study, were evaluated using precision, recall, and f-measure metrics for a set containing only one symptom pool for each class. The authors of [28] have proposed the use of an enhanced CNN technique to detect rice disease. DNNs have had a lot of success with image classification tasks. In this study, they have demonstrated how DNNs can be used for plant disease detection in the context of image classification. Finally, this research compares existing techniques in terms of accuracy of 80%, 85%, 90%, and 95% for TL, CNN + TL, ANN, and ECNN + GA techniques, respectively. The work in [29] has addressed numerous ML and DL techniques. SVM, KNN, RF, LR, and CNN were the ML approaches used in the study effort for disease prediction in plants. Then, a comparison of ML and DL approaches was carried out. Among the ML techniques, the RF has the best accuracy of 97.12%; however, when compared to the DL model presented in the study, the CNN technique has the highest accuracy of 98.43%.

The capacity to identify rice leaf disease was limited by the image backgrounds and the conditions under which the images were acquired [30]. DL models for automated identification of rice leaf diseases suffer significantly when evaluated on independent rice leaf disease data. The results of well-known and frequently used TL models for detecting rice leaf disease were examined in this study. There were two methods for accomplishing this: frozen layers and fine-tuning. The DenseNet169 findings produced an excellent testing accuracy of 99.66%, and when the results of the fine-tuned TL models were analyzed, Xception performed well and achieved 99.99% testing accuracy. The authors of [31] have presented Ant Colony Optimization with Convolution Neural Network (ACO-CNN), a novel DL technique for disease detection and classification. ACO was used to assess the effectiveness of disease diagnostics in plant leaves. The CNN classifier was used to sub- tract color, texture, and plant leaf arrangement geometries from the given images. Some of the effectiveness metrics used for analysis and providing a proposed method demonstrate that the proposed approach outperforms previous techniques with an accuracy rate. Aoncert measurements were utilized for the execution of these approaches. Finally, the ACO-CNN model outperformed the C-GAN, CNN, and SGD models in terms of accuracy, precision, recall, and f1-score. The accuracy rates of C-GAN, CNN, and SGD were 99.6%, 99.97%, and 85%, respectively. The accuracy rate in the ACO-CNN model was 99.98%; therefore, precision, recall, and F1-score have higher rates in the ACO-CNN technique compared to other models, and the F1-score has the highest rate compared to other models.

The authors of [32] have presented a DL model (PPLCNet) that includes dilated convolution, a multi-level attention mechanism, and GAP layers. The model used novel weather data augmentation to expand the sample size to enhance the generalization and robustness of feature extraction. The feature extraction network uses saw-tooth dilated convolution with a configurable expansion rate to extend the perceptual field of the convolutional domain, effectively addressing the problems of insufficient data information extraction. The lightweight CBAM attention mechanism was located in the feature extraction network’s middle layer. It was used to improve the model’s information representation. By reducing the number and complexity of parameters computed by the network, the GAP layer prevents overfitting of the model. The validation of the retained test dataset reveals that the PPLC-Net model's recognition accuracy and F1-score were 99.702% and 98.442%, respectively, and that the number of parameters and FLOPs were 15.486 M and 5.338G, respectively, which can meet the requirements of accurate and fast recognition. Furthermore, the proposed integrated CAM visualization approach fully validates the efficiency of the proposed model.

Proposed Method

A. Image Acquisition

The plant-Village dataset provides 4,062 images of plant leaves displaying common symptoms. In this dataset, 1,180 images were found to be affected by Black Rot, 1,383 by Esca measles, 1,076 by Leaf spot, and 423 by healthy leaves, all with a resolution of 256 × 256 pixels. A leaf with black rot, a leaf with black measles, a leaf with blight, and a healthy leaf is displayed in Fig. 1. The data set contains varying quantities of images for each category, indicating significant imbalances. Esca is the most common classification, accounting for roughly 34% of the images, while Black Rot and Leaf Blight make up 29% and 26% respectively. There are also 1076 Healthy images and 10.4% Normal images in the collection.

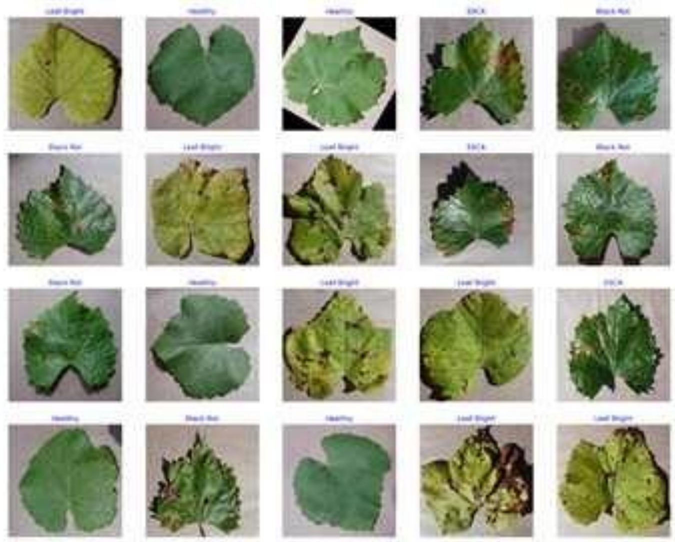

Fig. 1: Sample images from dataset,

Table I: List of Parameters Used For Image Enhancement

Enhancement method	Parameters
gaussian filter	sigma-range(0.4,1.3)
mean filter	kernel-size-range(3,5)
median filter	kernel-size-range(2,5)
image acutance	alpha-range(0,0,2)
brightness	gamma(2.0)
contrast	alpha(1.0)

B. Image Pre-processing and Augmentation

The size of the dataset must be increased by using data augmentation techniques in order to prepare plant leaves disease images for disease identification. Training the recognition model in this way ensures that it will be more resilient and can generalize more effectively. Using standard data augmentation methods, the experiment compared the effectiveness of the data augmentation method proposed in this study. The traditional methods included flipping the im- age horizontally and vertically, rotating the image, applying different types of filtering (Gaussian, mean, and median) with a probability of 0.2, enhancing image contrast, sharpening images with a probability of 0.3, and adjusting image brightness. According to Table I, the parameters used for each image enhancement method are listed. Table II provides more details about the dataset and can be accessed at https://www.kaggle.com/datasets/rm1000/augmented-plant- disease-detection-dataset.

C. Proposed Methodology for Plant Leaf Disease Detection

This study focuses on the detection of plant leaf diseases using faster-rcnn. The training process for this model to detect diseases in plant leaves is depicted in Fig. 2. The process begins with inputting the selected plant leaf disease images. Next, classification features are extracted from the input images. Output is then derived from the findings of disease identification using the faster-rcnn model.

Table II: Information about the Dataset

Class	No of images without augmentation	No of images with augmentation
Healthy	423	3000
Esca measles	1383	3000
Leaf spot	1076	3000
Black rot	1180	3000
Total	4062	12000

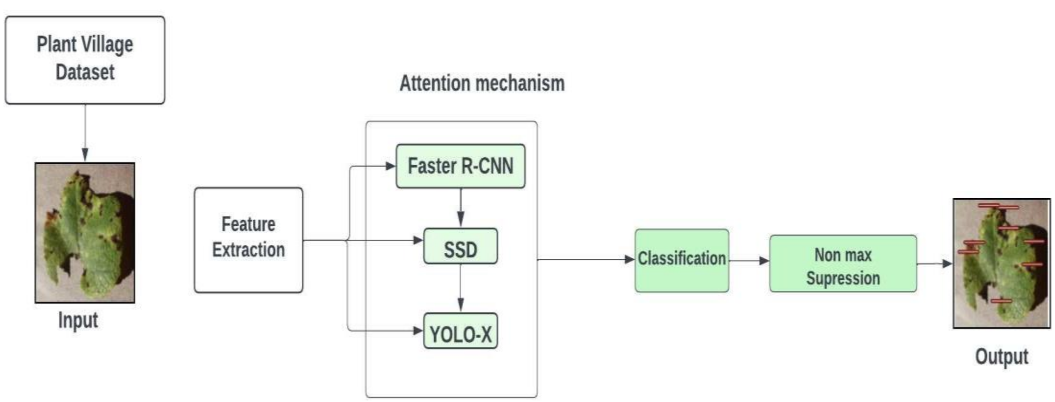

Fig. 2: Proposed attention model for plant disease detection.

A loss function is used throughout to quantify the degree to which the projected disease species deviates from the true disease species. This enables the models to learn and improve their detection accuracy over time. The optimization of the final output result is achieved through the utilization of the Adam optimizer, a widely used optimization algorithm in deep learning.

By following this approach, the study aims to leverage the capabilities of faster-rcnn, model to detect plant leaf diseases effectively. The training flow chart provides a systematic framework for the feature extraction and disease detection process, facilitating the accurate identification of different disease species in plant leaves.

D. Attention Mechanism Models

The study utilizes attention mechanism: “Squeeze & Excitation” spatial attention mechanism. We chose the SE attention mechanism because it is simple and adds only a few new parameters.

Squeeze & Excitation Attention: In order to extract features, the SE channel attention mechanism employs the CNN channel. It requires re-calibrating features so that the model can pick up and remember relevant details from all of the available feature channels. Fig. 3 depicts the two steps involved in this mechanism: squeezing and excitement. After the feature image has been spatially compressed using the squeeze technique, the feature channel’s relative relevance can be determined using the excitation technique; a model is created based on the correlation between the channels. In doing so, the original feature images are excited into matching channels. The SE mechanism has few additional parameters and is computationally simple.

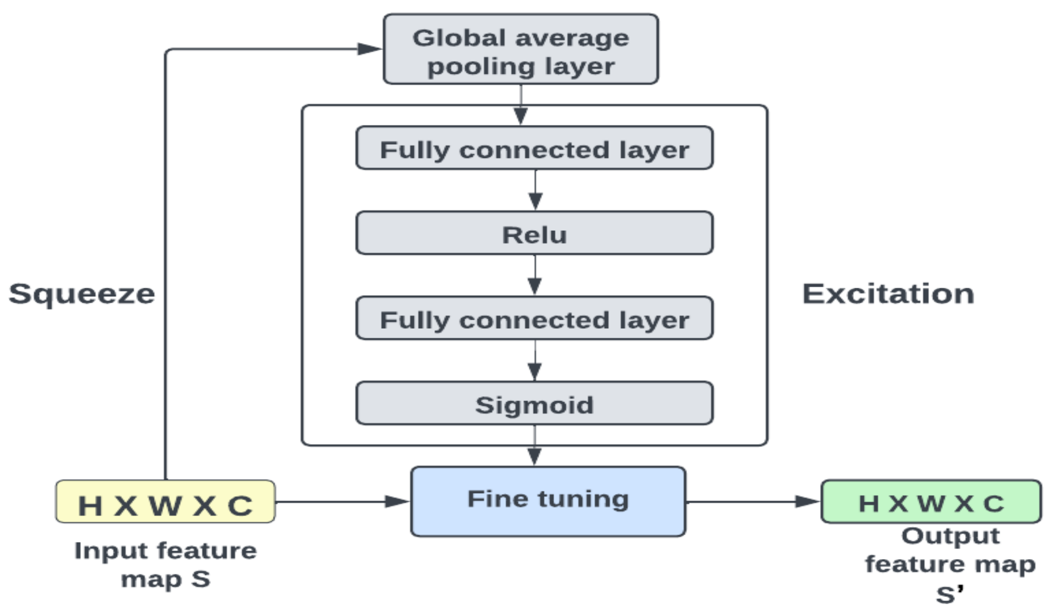

Fig. 3: SE attention mechanism.

E. Dection Models for Disease Detection in Plant Leaves with Attention Mechanism

CNN-based object detection can be categorized into two main types. The first type uses a regional proposal to detect objects. This involves identifying candidate regions in the image, which are then divided to detect objects. This two- stage approach is exemplified by methods such as “R—CNN”, “Fast(R-CNN)”, &

"Faster (R-CNN)". The second type of object detection does not use a regional proposal and is referred to as one-stage object detection. An image is analyzed based on a CNN prediction of an object's position & properties.

The study model, namely the "Faster R–CNN model" for detecting plant leaves disease. The input of the selected plant leaf disease images, extraction of classification features, and use of the three disease detection models were involved in the process. The output was an analysis of the disease detection results. For optimizing the final output, an Adam optimizer was used to predict the difference between reality and the prediction of disease species. Researchers found that the" Faster(R-CNN)" model boosts high detection accuracy and can detect targets end-to-end. However, its running speed is relatively slow. The characteristics of this model are elaborated as follows:

1) Plant Leaves Disease Detection using Faster (R-CNN) Model: This model is comprised of three main components: the "Extraction of features", the "Region Proposal Network", and the "Region with Convolutional Neural Network Features". Fig. 4 depicts the Faster (R-CNN) model with attention techniques. A Faster (R-CNN) method is used to detect plant leaf diseases in four primary steps: generating candidate disease regions, extracting disease characteristics, categorizing the disease, and performing bounding box regression. The Faster (R-CNN) model utilizes convolutional neural networks for the extraction of features and then generates feature maps for corresponding images. However, the convolution kernel's inherent locality means that only local information of disease images is retained, leading to information loss and reduced detection accuracy. To address this issue, the study introduced attention mechanisms, namely SE, ECA, and CBAM, without changing the feature extraction network's structure or backbone features. As a result of forward propagation after the last identity block, these mechanisms were introduced to enhance the model.

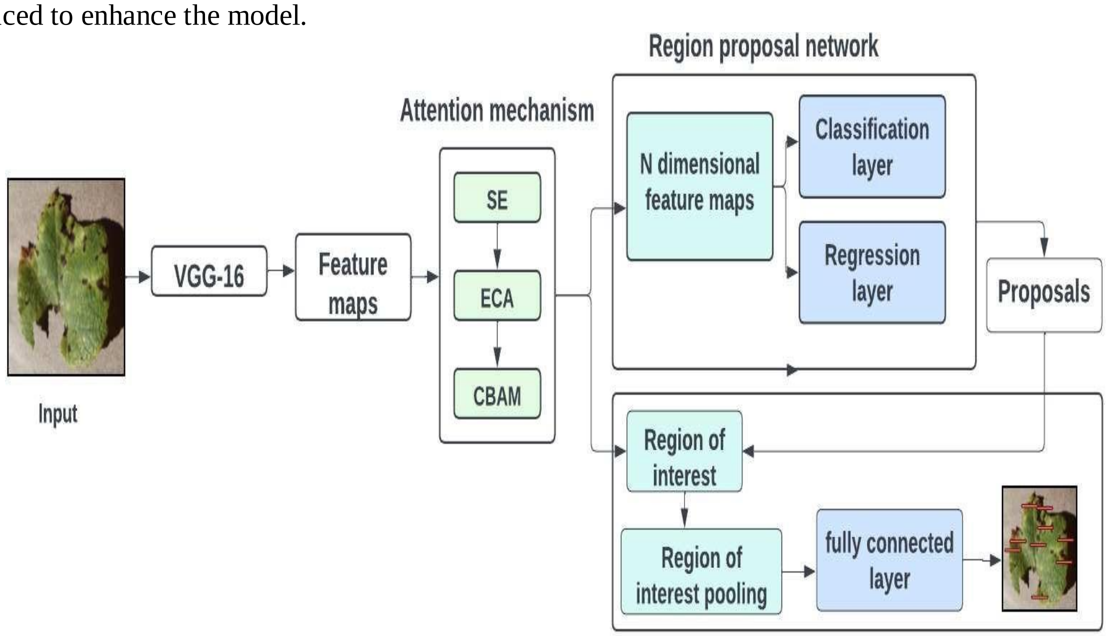

Fig. 4: Faster (R-CNN) model with attention techniques.

Results and Discussions

A. Evaluation Metrics

Results were evaluated based on standard measures for evaluating target detection. One class of targets will be evaluated using ”Precision,” ”Recall,” ”Average Precision,” and ”Mean Average Precision,” while all targets will be evaluated using ”Mean Average Precision.” However, in this study, we evaluated the plant leaf disease detection model’s performance on a wider set of metrics, including the mean absolute percentage (mAP), the frame rate (FPS), the parameters, and the precision (P) and recall (R) values. The Eq. 1, 2 and 3 were used to calculate P, R, and F1.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} * 100 \quad (1)$$

$$Recall = \frac{(TruePositives)}{(TruePositives + FalseNegatives)} * 100 \quad (2)$$

$$F1score = \frac{(2 * Precision.Recall)}{(Precision + Recall)} \quad (3)$$

In Eq. 4, the variables P, TP, FP, R, FN, and F1 represent various metrics used to evaluate the performance of a model. P is the precision, which measures the percentage of correct positive predictions. The probability that plant disease leaves are accurately detected is denoted by true positives (’TP’), whereas the probability that they are mistakenly categorized as positive is denoted by false positives (’FP’). Recall, or the proportion of true positives that were correctly detected, is denoted by the letter R. The likelihood of mislabeling a positive sample as negative is known as the ”Fasle negatives” (’FN’) rate. F1 is a measure of accuracy that is the harmonic mean of two other metrics, recall and precision.

$$\int_0^1 PRdR \quad (4)$$

A higher value for TP indicates a more accurate prediction & better performance of the model. A model’s performance can be measured using mAP, which is a metric that averages the average precision of all diseases. Eq. 5 defines mAP as the average of all AP values. FPS stands for the number of pictures handled each second. The algorithm’s ability to recognize items improves as the FPS increases.

$$mAP = \frac{1}{N}\sum_{m=1}^{N} AP \quad (5)$$

B. Experiment Results and Analysis

The plant disease dataset was utilized to compare the Faster(R-CNN), model with the classical versions based on different attention mechanisms. The models were all trained and detected with the same configuration information and training platform.

Faster (R-CNN) Result Analysis: The “Faster(R-CNN)” model can be combined with different attention mechanisms to create different versions. Also we have combined the three attention mechanisms i.e. Faster (R-CNN) with SE Attention. To test their performance in detecting plant diseases, all these versions were used in the same experimental setup, and the results are presented in Table III and in Fig. 5. Table III presents a comparison between the Faster (R-CNN) model and four modified versions: “Faster (R-CNN) with SE Attention”, “Faster (R-CNN) with ECA Attention”, and “Faster (R-CNN) with CBAM Attention”. The results indicate that the Faster (R-CNN) with SE Attention model outperformed the original model with an increase in P, R, and F1 values by 4.74%, 9.81%, and 7.22% respectively, and an increase in mAP by 6.27%. Similarly, the Faster (R-CNN) with ECA Attention model showed improvements over the original model with an increase in P, R, and F1 values by 1.48%, 4.29%, and 2.87% respectively, and an increase in mAP by 2.81%. Finally, the "Faster (R-CNN) with CBAM Attention" model showed slight improvements over the original model with an increase in P, R, and F1 values by 0.69%, 1.47%, and 1.08% respectively, and an increase in mAP by 0.53%.

Table III: Comparison Analysis of Faster (R-Cnn) Models with Different Attention Techniques

Model	Precision	Recall	F1-Score	mAP
Faster (R-CNN) model	75.06	74.42	74.74	79.12
Faster (R-CNN) with SE Attention	79.80	84.23	81.96	85.39
Faster (R-CNN) with ECA Attention	76.54	78.71	77.61	81.93
Faster (R-CNN) with CBAM Attention	75.75	75.89	75.82	79.65
Faster (R-CNN) with SE, ECA,CBAM Attention	84.52	86.32	80.79	84.31

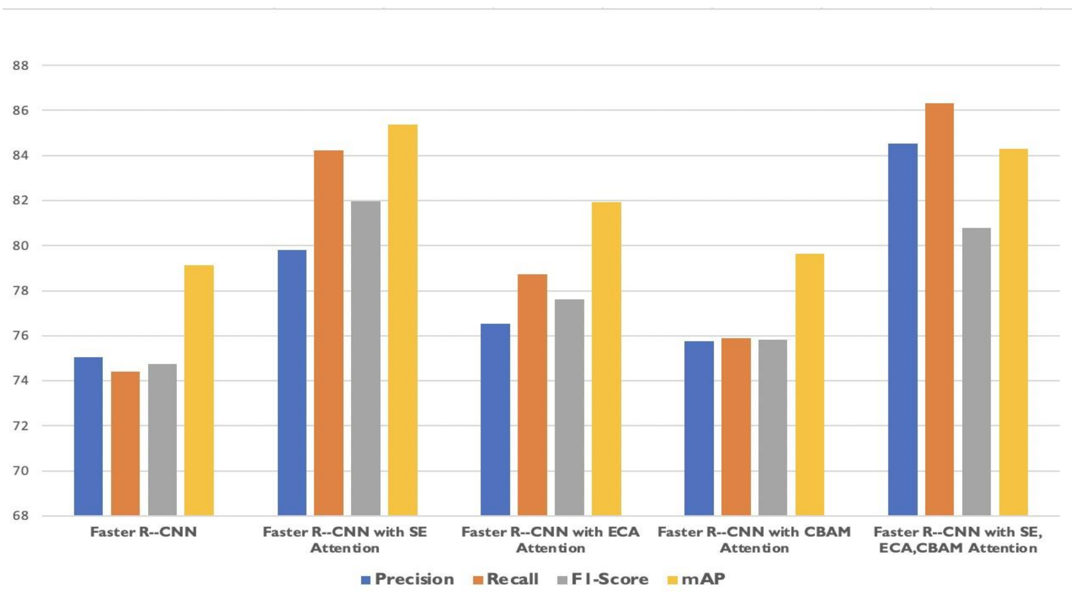

Fig. 5: Comparison analysis of Faster (R-CNN) models with different attention techniques.

Based on the analysis above, it is evident that the performance of Faster (R-CNN) improved after the inclusion of attention mechanisms, despite a slight increase in parameters for "Faster (R-CNN) with SE Attention and Faster (R-CNN) with CBAM Attention". Enhanced precision and accelerated speed of detection are achieved through the attention mechanism for plant leaves images. Among the various models, "Faster (R-CNN) with SE, ECA, and CBAM Attention" displayed the best detection effect when compared with "Faster (R-CNN) with SE Attention". The "Faster (R-CNN) with SE Attention" model demonstrated a 3.26%, 5.52%, and 4.35% increase in P, R, and F1 values, respectively, with an increase of 3.46% in mAP. In comparison with" Faster (R-CNN) with CBAM Attention"," Faster (R-CNN) with SE Attention" increased P, R, and F1 by respectively 4.05%, 8.34%, and 6.14%. When precision is considered, the" Faster (R-CNN) with SE, ECA, and CBAM Attention" model shows optimal results. It focuses on channel features with the most significant information while suppressing un-important features, making it ideal for detecting plant diseases in the dataset.

Conclusion

In this study, we proposed a novel classification approach for plant disease detection leveraging various attention deep learning techniques. Our approach demonstrated significant improvements in accuracy and efficiency over traditional methods, showcasing the potential of attention mechanisms in enhancing deep learning models for complex image classification tasks. By focusing on the critical regions of plant leaves and effectively distinguishing between healthy and diseased states, our model achieved superior performance metrics, indicating its applicability in real-world agricultural scenarios. After initial screening, disease detection models were selected and their performance was compared. The results of the foregoing investigation demonstrated that the" Faster(R- CNN)," model, when enhanced with numerous attention mechanisms, provided the most accurate detection results. Overall," Faster (R-CNN)" models exhibited the lowest detection precision, the slowest operating speed, and the most parameters of the three types of models. Despite the promising results, several avenues for future research remain open. Firstly, expanding the dataset to include a wider variety of plants and diseases would enhance the model's generalizability and robustness. Additionally, integrating multi-modal data, such as environmental factors and soil conditions, could further improve prediction accuracy. Exploring more advanced attention mechanisms, such as self-supervised learning and transformer-based architectures, may yield even better results. Finally, developing a user-friendly mobile application that incorporates our model would facilitate its adoption by farmers and agricultural professionals, promoting more widespread and practical use of this technology in disease management and prevention.

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