JOURNAL OF BASIC SCIENCE AND ENGINEERING

Segmentation And Classification of Plant Leaf Disease Using Advanced Deep Learning Approach and Ensemble Classifier

Suma S H [1], K. Prabhushetty [2], Jagadish S. Jakati [3]

[1] Research Scholar, Department of Electronics & Communication Engineering, S G Balekundri Institute of Technology Shivbasavnagar, Belagavi-590010, VTU, Karanatak, India.
[2] Professor and Research Supervisor, Dept. of Electronics and Communication Engineering Veerappa Nisty Engineering College Hasanapur, India
[3] Assistant Professor, School of computer science Engineering and Applications, D. Y. Patil International University Akurdi, Pune, Maharashtra 411044, India,

DOI: https://doie.org/10.0714/Jbse.2024192880

***Abstract*—** Plants play a crucial role in sustaining the world's food production. However, the occurrence of various plant diseases poses a threat to crop yields, leading to significant losses if not managed effectively. The traditional approach of manually monitoring plant diseases by agricultural experts and botanists is laborious, demanding, and prone to errors. To mitigate the impact of plant diseases, there is a growing recognition of the potential of machine vision technology combined with artificial intelligence. By automating disease detection and analysis, AI can provide faster and more precise assessments compared to traditional methods. This technological advancement offers a promising solution to reducing the severity of diseases and minimizing crop losses. Recently, deep learning-based methods have gained huge attention from research community in this context of image processing tasks. Therefore, in this work, we present a deep learning enabled ensemble machine learning approach for plant disease classification. The first phase of the work performs data augmentation, in next stage, we present modified Mask RCNN model for plant leaf segmentation. Later, a CNN based model is presented to extract the deep features. Finally, SVM, Random Forest and Decision Tree are used to construct the ensemble classifier with the help of majority voting. The performance of proposed approach is validated on Plant Village, Apple, Maize, and Rice where overall accuracy is obtained as 99.45%, 96.30%, 96.85%, and 98.25%, respectively

Keywords: Plant disease, CNN Mask-RCNN, SVM, ensemble, classification, Machine Learning, Deep Learning.

1. INTRODUCTION

Plants constitute essential components of worldwide biodiversity, fulfilling crucial roles in safeguarding human well-being. It is imperative to meticulously examine the history and developmental processes of plants. Due to the growing population, the demand of plant-based foods has increased drastically. Therefore, agriculture is widely promoted and adopted as business in numerous countries. Despite of this increase, the food supply is not met. The Food and Agriculture Organization (FAO) of the United Nations revealed that the global population suffering from starvation has been steadily increasing since 2015 [1]. Current estimates indicate that approximately 680 million people are experiencing starvation, constituting less than 9% of the global population. This represents an increase of 10 million within a year and approximately 120 million over a decade. Moreover, over 85% of the world's population relies on agriculture [2]. Farmers play a pivotal role in producing 80% of the world's food [3]. Unfortunately, more than half of crop yields are lost annually due to plant diseases and pests [4]. Hence, it is imperative to swiftly and accurately identify and detect plant diseases.

The plant diseases have severe impact on human life. However, detecting diseases in plants within vast fields poses a significant challenge, requiring trained personnel and optical leaf examinations [4]. Farmers rely on naked-eye observations of symptoms on plant leaves and diagnose diseases based on their experience, a process that is labour-intensive, time-consuming, and demands specialized skills [5]. Therefore, the main aim of this work is to develop an automated mechanism which can help non-pathologist and non-botanists to detect and identify the plant diseases.

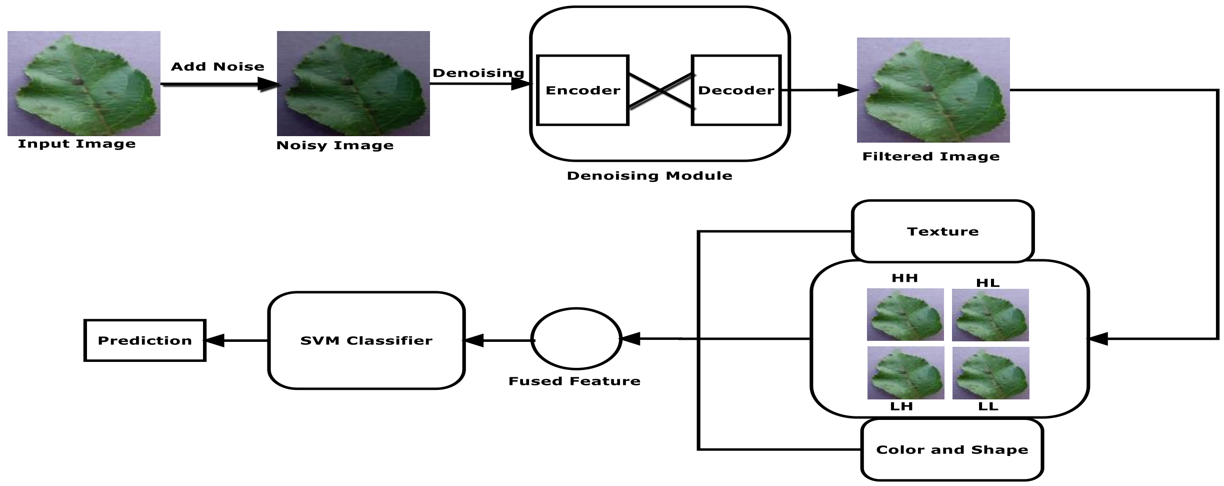

Fig. 1. General architecture of Plant Disease Classification [1].

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

Several methods have been developed based on this concept such as Shrivastava et al. [8] presented color feature extraction-based system for rice plant disease detection and trained support vector machine-based classification model. Harakannanavar et al. [9] presented ML based approach where image pre-processing includes histogram equalization to improve the image quality, and K-means clustering. The feature extraction phase includes Discrete Wavelet Transform, Principal Component Analysis and Grey Level Co-occurrence Matrix descriptors. These obtained features are used to train different classifiers. Basavaiah et al. [10] developed a multiple feature extraction and fusion approach where color histogram, Hu moments, Haralick and local binary patterns are used as feature extraction model. The obtained feature set is then used to train the random forest and decision tree classifiers. Despite of several advancements, these methods suffer from challenging issues such as overfitting, class imbalance, generalization of model, and training complexities.

To overcome these issues, deep learning-based methods have been introduced for image segmentation and classification. Upadhyay et al. [11] developed a DL based model which considers image size, shape and color as important features. It also utilizes Otsu's global thresholding technique to remove background noise and produce binary image. Finally, a fully connected CNN is applied to perform the classification. The CNN stands out as the predominant classifier in image recognition, demonstrating remarkable proficiency in image processing and classification [12]. Initial forays into deep learning techniques for plant image recognition were centered on leaf vein patterns [13]. Utilizing a 3–6-layer CNN, researchers successfully classified three leguminous plant species: white bean, red bean, and soybean. Mohanty et al. [14] further advanced deep learning methodologies by training a model to identify 14 crop species and 26 crop diseases, achieving an impressive accuracy of 99.35% on the test dataset. Ma et al. [15] employed a deep CNN to undertake symptom-wise recognition of four cucumber diseases—downy mildew, anthracnose, powdery mildew, and target leaf spots—with recognition accuracy reaching 93.4%. Additionally, Kawasaki et al. [16] presented a CNN-based system for recognizing cucumber leaf disease, achieving an accuracy of 94.9%.

The traditional methods have not worked much on plant leaf segmentation which leads to raise ambiguity in leaf background and foreground data. In this work, we adopt deep learning-based solution for plant leaf image segmentation. Later, deep learning-based CNN architecture is used to extract the features. Finally, an ensemble classifier is constructed by using SVM, Random Forest and decision tree classifier and majority voting methods is applied to obtain the final classification outcome.

Rest of the article is organized in following sections: section II presents the brief literature review about existing approaches of plant disease classification, section III presents the detailed discussion about proposed model, section IV presents the outcome of proposed approach and comparative analysis with existing methods, finally, section V presents the concluding remarks about the work.

2. LITERATURE REVEIW

In this section, we discuss about existing methods of plant disease detection, prediction and classification. as discussed before, the machine and deep learning methods are widely adopted in this field to automate the complete process.

Guo et al. [17] used deep learning based mathematical model for plant disease detection and recognition. The first phase of this uses region proposal network (RPN) to localize the plant leaves in the complex surrounding region. In next stage, leaves are segmented and given as input to the transfer learning model which is trained by the diseased leaves dataset with simple background. This method has reported the overall accuracy as 83.57% which shows the significance of deep learning model. Saleem et al. [18] emphasized on meta-architectures of deep learning approach including Single Shot MultiBox

Detector (SSD), Faster Region-based Convolutional Neural Network (RCNN), and Region-based Fully Convolutional Networks (RFCN) were applied with the help of Tensorflow object detection framework. The SSD model is trained with Adam optimizer and it shows highest mean average precision as 73.07%

Similarly, in [19] Roy et al. introduced DL based model for multi-class classification. this article is based on the YoloV4 model. The complete image is divided into multiple grids then bounding boxes and their corresponding confidence scores are computed and class probability map is also estimate. In order to perform these tasks, this model uses Dense-CSPDarkNet53 and output of this module is fed to the modified PA Net architecture and finally, Head module produces detection results.

Chug et al. [20] developed a hybrid deep learning model where eight different pre-trained deep learning models are used including Efficient Net B0 to B7 for feature extraction and five different ML models are used as classifier including k-Nearest Neighbors (kNN), AdaBoost, Random Forest (RF), Logistic Regression (LR), and Stochastic Gradient Boosting as classifiers

Plant leaf image segmentation also plays important role to improve the classification performance therefore several segmentation methods have been introduced. In image segmentation tasks, the UNet model has shown some significant outcomes therefor it is widely adopted in various applications. Bhagat et al. [21] used UNet approach and developed UNet based model for plant leaf segmentation. Moreover, this architecture uses EfficientNet-B4 as an encoder model to extract the features. However, information degradation is a crucial challenge for these models therefore authors have redesigned the skip connection and residual blocks in the decoder module. It helps to reduce the computational complexity of the model. The decoder model generates low- and high-level attributes which are combined together with the help of output layer to improve the segmentation performance.

Yang et al. [22] used deep learning-based model for leaf image segmentation from complex background and also incorporated leaf classification model by using deep learning model. This model uses Mask RCNN model which performs two main tasks as feature map generation, and classification with bounding box regression. The segmentation map generation part uses ResNet-FPN to produce the feature map. In next stage, the obtained feature map is processed through the classification part where ROI alignment is performed and finally, the bounding box regression and classification is applied.

Yang et al. [23] reported that the complex background has severe impacts on the segmentation and classification. These problems include noise interference, overlapping objects, and illumination variations etc. To overcome these issues, authors have introduced Mask RCNN and dual channel convolution neural network. it also uses soft non-maximum suppression algorithm to enhance the detection performance for overlapping object scenarios. Similarly, the next step includes pooling operations which helps to reduce the loss during alignment of feature map and original image. Finally, the mask filer layer is used to mask the complex backgrounds. This model replaces Softmax with support vector machine classifier (SVM) and then Adaptive Chaotic Particle Swarm optimization is used to optimize the overall performance.

3. PRAPOSED METHODOLOGY

This section presents the proposed solution for plant leaf segmentation using deep learning and machine learning based ensemble model to perform the classification. According to this approach, the first step is to load entire databased along with its labels. In next step, we perform data augmentation where image cropping, rotation, image blurring etc. operations are performed. In next stage, the deep learning-based segmentation module is deployed to segment the leaf images from complex backgrounds. This segmented image is then used in feature extraction phase where different feature extraction models are used to obtain the robust feature map. Finally, an ensemble classifier is developed to learn the complex patterns and classify them with improved accuracy. below given subsections present the detailed discussion about each stage.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

3.1.1. Data Preprocessing and augmentation

In pre-processing, we resize the image data in 256x256 row and column matrix and convert is to Grayscale. Further, data augmentation methods are applied. Image data augmentation methods are techniques used to increase the diversity and size of a dataset by applying various transformations to the original images. These transformations help improve the generalization and robustness of machine learning models. In this work, we have used following:

- Horizontal and Vertical Flipping: Flip the image horizontally or vertically. This can help make the model invariant to left-right or top-bottom orientation.
- Rotation: Rotate the image by a certain angle, typically randomly chosen between a specified range. This helps the model become more robust to variations in object orientation.
- Scaling: Resize the image by zooming in or out. This can help the model learn to recognize objects at different scales.
- Translation: Shift the image horizontally and/or vertically. This helps the model become invariant to small changes in object position.
- Brightness and Contrast Adjustment: Adjust the brightness and contrast of the image. This helps the model become more robust to changes in lighting conditions.
- Noise Injection: Add random noise to the image. This can help the model become more robust to noise in real-world images.

This preprocessing ensures that the dataset is clean, consistent, and ready for plant leaf segmentation.

3.1.2. Deep learning for plant leaf segmentation.

This section presents the proposed deep learning-based segmentation model for plant leaf segmentation. The existing methods have reported that the leaf segmentation models suffer from several challenges such as noise, illumination variations. Therefore, we focused on development of a robust approach for segmentation. The proposed segmentation model uses instance segmentation approach known a Mask RCNN. This model can perform pixel-level object segmentation and target recognition. The architecture of Mask RCNN not only preserves the foundational structure of Faster RCNN but also incorporates additional components such as the Feature Pyramid Network (FPN) and the Region of Interest Alignment algorithm (ROIAlign). Its primary framework comprises six key segments: Input, backbone feature extraction network, FPN, Region Proposal Network (RPN), ROIAlign, and the output for bounding box, class, and mask predictions (Box, Class, Mask). Below given figure depicts the overall architecture of Mask RCNN.

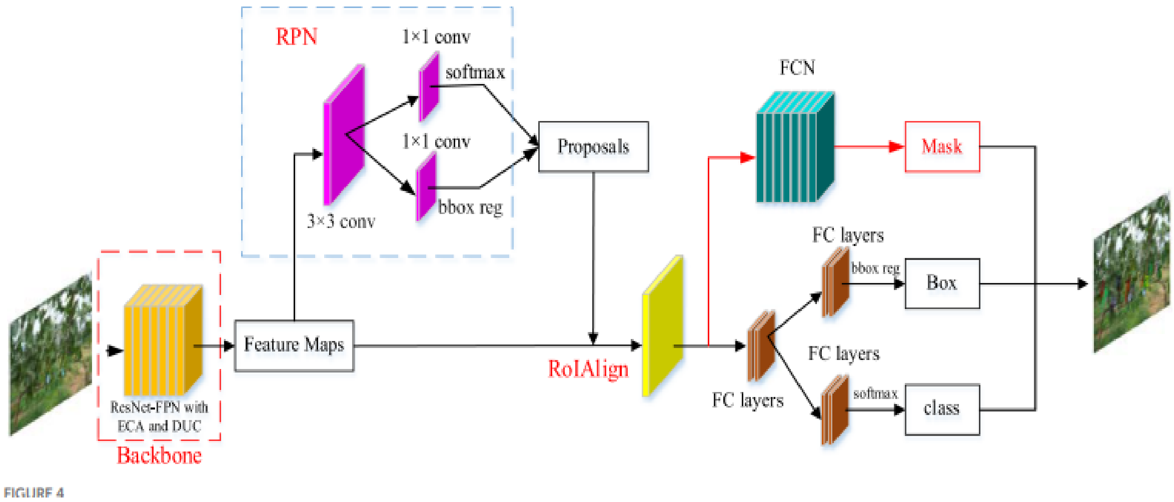

Fig.2. Overall architecture of Mask RCNN[2].

In this context of plant disease detection, the segmentation plays important role. According to this process of Mask RCNN, the input image containing plant leaves is fed into the ResNet50 + FPN

ISSN: 1005-0930

network model to extract relevant features and generate feature maps specific to the leaves. These feature maps aid in identifying potential regions of interest (ROIs), which in this case correspond to individual plant leaves, through the Region Proposal Network (RPN). Following the identification of ROIs, a SoftMax classifier is applied to distinguish between leaf and non-leaf areas within these regions. To refine the accuracy of leaf boundaries, frame regression techniques are employed. Moreover, redundant ROIs are pruned using non-maximum suppression, ensuring a streamlined selection of relevant leaf regions. Subsequently, the feature maps along with the refined ROIs undergo processing in the RoIAlign layer. This layer facilitates the creation of standardized feature maps for each leaf region, enabling consistent segmentation across different leaf sizes and shapes. Finally, the flow branches into two paths: one branch proceeds to a fully connected layer for leaf classification and boundary refinement, while the other branch feeds into a full convolutional network (FCN) specialized in pixel-level segmentation. This dual-branch approach ensures comprehensive segmentation of plant leaves, providing both high-level categorization and detailed pixel-wise delineation.

Generally, the backbone module of this architecture uses ResNet101 architecture which has total 101 layers. However, in this work we have considered plant leaf images where applying ResNet101 can reduce the operation speed drastically. Therefore, we have used ResNet50 in this work. Moreover, the considered data has large difference in size due to different types of plant leaves therefore the simple convolution network is not capable to extract the detailed attributes from these images. Therefore, we have considered feature pyramid network (FPN) to improve the feature extraction process. The FPN employs a hierarchical structure with horizontal connections, facilitating the creation of a network feature pyramid from a single-scale input. This approach effectively addresses the challenge of extracting target objects across multiple scales from images while minimizing the parameter count. FPN is inspired by the Feature Map utilized in the pyramid structure of SSD (Single Shot MultiBox Detector). However, unlike SSD, FPN incorporates not only deep Feature Maps from networks like VGG but also integrates shallow Feature Maps. FPN optimizes the integration of these Feature Maps through a combination of bottom-up, top-down, and lateral connections. This comprehensive approach ensures efficient information flow across different levels of abstraction, enhancing detection accuracy without significantly increasing processing time. By leveraging both deep and shallow Feature Maps in a cohesive manner, FPN effectively tackles the multi-scale object detection challenge, making it a powerful tool for various computer vision tasks.

However, the complex nature of plant leaf images poses several challenges for Mask RCNN models. In order to overcome this issue, we focus on incorporating attention mechanism that enables the model to concentrate on and amplify valuable feature information while filtering out irrelevant features. This targeted focus enhances the model's resilience to variations in field environments, ultimately improving its performance and adaptability across diverse conditions. In this work, we have used channel attention mechanism with upsampling convolution in backbone model of Mask RCNN. The updated architecture of backbone model is depicted in figure 3.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

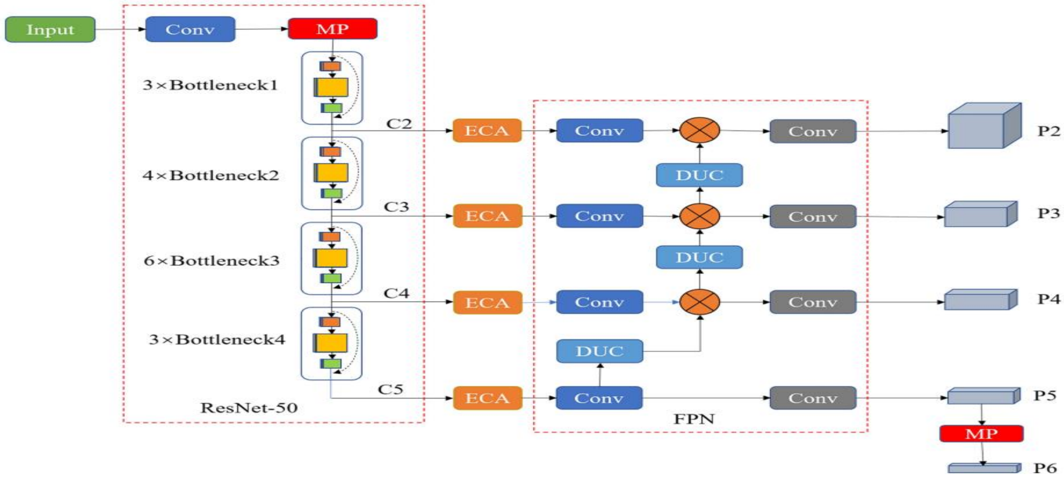

Fig. 3. Improved Backbone architecture[3].

The architecture of channel attention model is depicted in figure 3. The primary concept revolves around introducing a local cross-channel interaction strategy devoid of dimensionality reduction. This strategy aims to capture interaction information among channels locally by examining each channel alongside its k-nearest neighbors post-global average pooling (GAP) of channels. Initially, the ECA module computes the input feature map with dimensions H×W×C (where C represents the number of feature channels) using GAP, resulting in a feature vector of size 1×1×C to encompass a global receptive field. Subsequently, cross-channel interaction information is captured through 1D convolution using a convolution kernel size of k. the size of convolution kernel k is related to the number of input channels and it can be selected as:

$$\psi(C) = \left|\frac{log_2(C)}{\gamma} + \frac{b}{\gamma}\right|_{odd} \qquad (1)$$

where C represents the number of input channels, γ and b values are set to 2 and 1, respectively. It helps to obtain the coverage of local cross channel interactions.

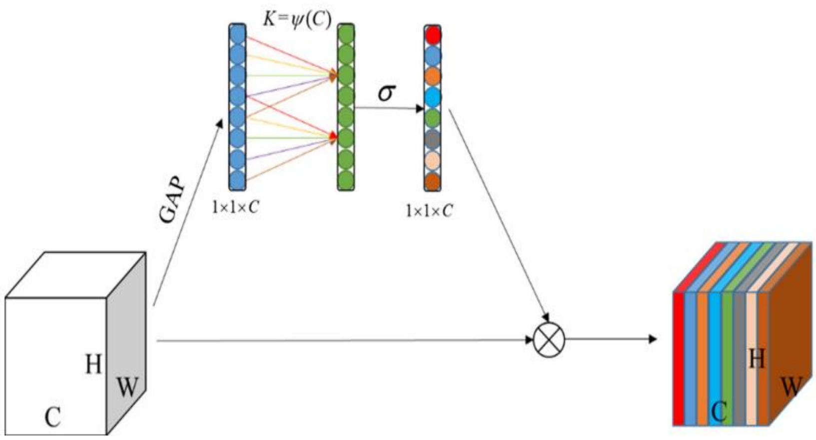

Fig. 4. Channel attention mechanism[4].

Later, sigmoid activation function is used to obtain the weights of each feature. In next step, the output feature channel weight vector undergoes multiplication with the original input feature map, thereby finalizing the original feature calibration along the channel dimension. This process enhances the directional nature of the extracted features and suppresses any invalid or ineffective feature channels. Consequently, this refinement boosts the extraction of meaningful and effective features.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

During the process of MaskRCNN, the FPN fuses the feature map from bottom up. However, the resolution of feature maps vary at different stages and depth parameters are also different for the obtained feature map. Therefore, upsampling operations need to be performed to obtain the feature maps of same size. The obtained feature set is then added pixel by pixel to obtain the feature fusion to construct the pyramid structure. The traditional MaskRCNN uses nearest neighbour interpolation for upsampling but it can lead to loss of detailed information of important features. To overcome this issue, we introduce a new upsampling approach where obtained feature maps (H/r×W/r×C) is fed as 3x3 convolutions for learning. The convolution operation produces a feature map of size H/r×W/r×(C×r^2) and reshaped as H×W×C where r is the ratio of upsample feature and original feature map size.

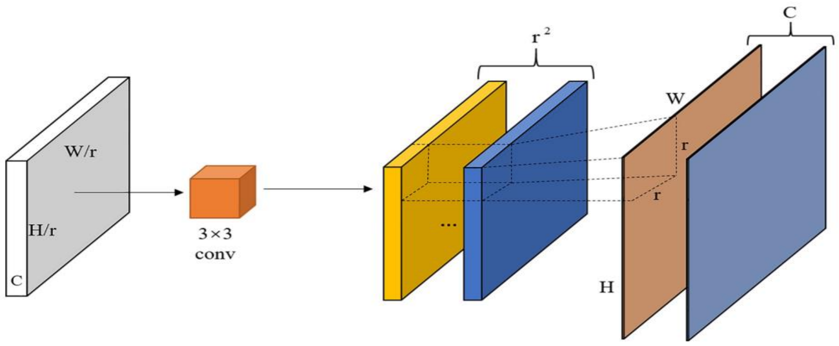

Fig .5. Upsampling model for feature extraction[5].

The final feature map is used to train the model for segmentation and classification. The classification model classifies the plant leaf category whereas the segmentation model generates the segmented output. The training process requires loss function modelling to improve the learning process and improving the segmentation outcome. The loss function is expressed as:

$$L = L_{cls} + L_{box} + L_{mask} \qquad (2)$$

Where L_{cls} represents the classification loss, L_{box} represents the regression loss of bounding box and L_{mask} is the mask loss.

3.2. Feature Extraction.

This subsection describes the proposed feature extraction model. The segmented leaf image is fed into the proposed feature extraction model. Rather than using traditional handcrafted feature extraction mode, we apply CNN based deep learning architecture for feature extraction. A deep learning model for image feature extraction typically involves convolutional neural networks (CNNs). CNNs are widely used for image-related tasks due to their ability to automatically learn relevant features from raw pixel data. The feature extraction of image data using CNN processes the image data through convolution layer, activation function, and pooling layer. Let's denote the input image as X and the output feature map of the lth convolutional layer as Hth. The mathematical formulation for the lth convolutional layer is as follows:

$$H_{i,j,k}^{(l)} = f^{(l)}\left(\sum_{m=1}^{M^{(l-1)}} \sum_{p=1}^{P^{(l)}} \sum_{q=1}^{Q^{(l)}} W_{p,q,m,k}^{l} . X_{(i+p-1),(j+q-1),m}^{(l-1)} + b_k^{(l)}\right) \qquad (3)$$

Where $H_{i,j,k}^{(l)}$ denotes the activation at position (i,j) in the k^{th} feature map of the l^{th} layer, $W_{p,q,m,k}^{l}$ represents the weight parameter of the k^{th} filter for the m^{th} input channel in the l^{th} layer, $X_{(i+p-1),(j+q-1),m}^{(l-1)}$ denotes the activation at position $(i+p-1),(j+q-1)$ in the m^{th} input channel of the $(l-1)^{th}$ layer, $b_k^{(l)}$ represents the bias term for the k^{th} filter in the l^{th} layer, and $f^{(l)}$denotes the activation function applied element-wise.In next step we apply ReLU activation function which is expressed as:

$$f^{(l)}(x) = \max(0, x) \qquad (4)$$

Further, pooling operations performed which reduces the spatial dimensions of the feature maps. It can be expressed as:

$$H_{i,j,k}^{(l)} = \max_{p=1}^{P^{(l)}} \max_{q=1}^{Q^{(l)}} \left(H_{(i-1)\times S^{(l)}+p,(j-1)\times S^{(l)}+q,k}^{(l-1)} \right) \qquad (5)$$

Where $S^{(l)}$ denotes the stride of pooling operation. After performing these operations, the features are flattened and fed into fully connected layer which can be expressed as:

$$H^{(l)} = f^{(l)}\left(W^{(l)}.H^{(l-1)} + b^{(l)}\right) \qquad (6)$$

Where $W^{(l)}$ represents the weight matrix of the l^{th} fully connected layer, $b^{(l)}i$s the bias vector. The obtained vector is considered as final feature vector.

3.3.ENSEMBLE CLASSIFICATION.

The final feature map is fed into the ensemble classifier model to classify the disease type. An ensemble classifier combines multiple individual classifiers to improve overall predictive performance. Let's consider that the ensemble classifier is denoted as E(x), where x represents the input data. Let us consider that we have N base classifiers denoted as C1, C2 ,...,CN. Each base classifier provides its prediction for a given input, which can be denoted as Ci (x), where i represents the index of the base classifier. There are various methods to combine the predictions of base classifiers to form the final prediction of the ensemble classifier. One commonly used method is majority voting, where the final prediction is determined by the majority vote of the base classifiers. Mathematically, the ensemble classifier E(x) can be represented as:

$$E(x) = argmax_y \sum_{i=1}^{N} \delta(C_i(x), y) \qquad (7)$$

Where y represents the possible classes, $\delta(.)$ Represents the Kronecker delta function which is 1 if two arguments are equal and 0 otherwise. In this work, we have used Support Vector Machine (SVM), Decision Tree (DT)and Random Forest (RF) classifier. The combined classifier is denoted by $E(x)$ which can be expressed as:

$$(x) = argmax_y \left(\sum_{i=1}^{N} \delta\left(C_{SVM_i}(x), y\right) + \sum_{i=1}^{N} \delta\left(C_{DT_j}(x), y\right) + \sum_{i=1}^{N} \delta\left(C_{RF_k}(x), y\right) \right) \qquad (8)$$

Where N represents the number of base classifiers and the final prediction $E(x)$ represents the obtained class that received most votes from the SVM, DT and RF classifiers. Below given figure 5 depicts the overall process of ensemble classification,

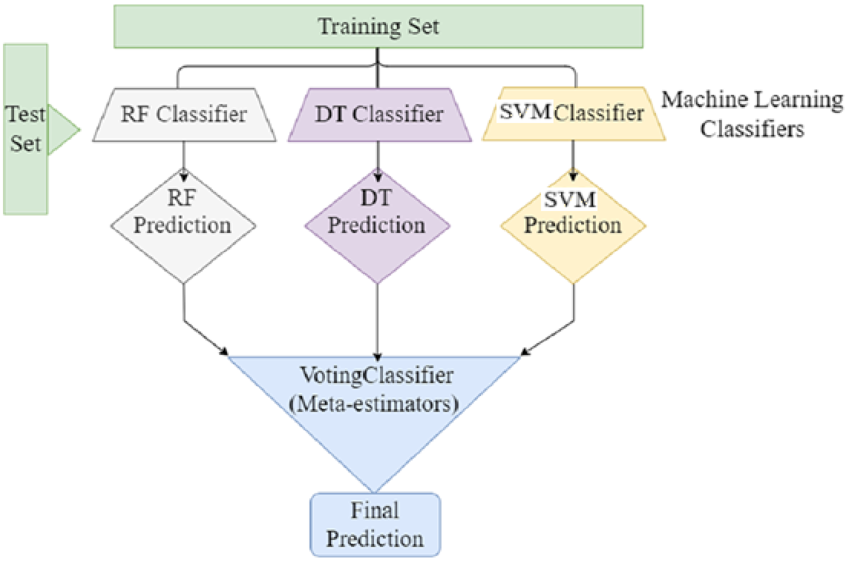

Fig.6. Ensemble classifier[6].

4. Results and Discussion

In this section, we present the outcome of proposed model and compare the obtained performance with state-of-art plant leaf and disease classification models. The first subsection presents the brief details about the dataset used in this work, next subsection describes the parameters used to measure the classification performance, finally, the comparative analysis is presented to show the robustness of proposed model.

4.1. Data Details

The Plant Village dataset is a comprehensive collection of images pertaining to various plant species and their associated diseases. This dataset contains 38 different disease classes and total of 54,305 images representing 14 different species. Figure 6 depicts the sample images of Plant Village dataset. The image related details in each category is depicted in table 1.

4.2.Sentiment Trends and Election Outcomes

The analysis of sentiment trends over time revealed significant correlations between public sentiment and election outcomes. By tracking sentiment polarity (positive, negative, neutral) for major candidates and political parties, the models were able to predict shifts in public opinion that corresponded with key events in the election cycle.

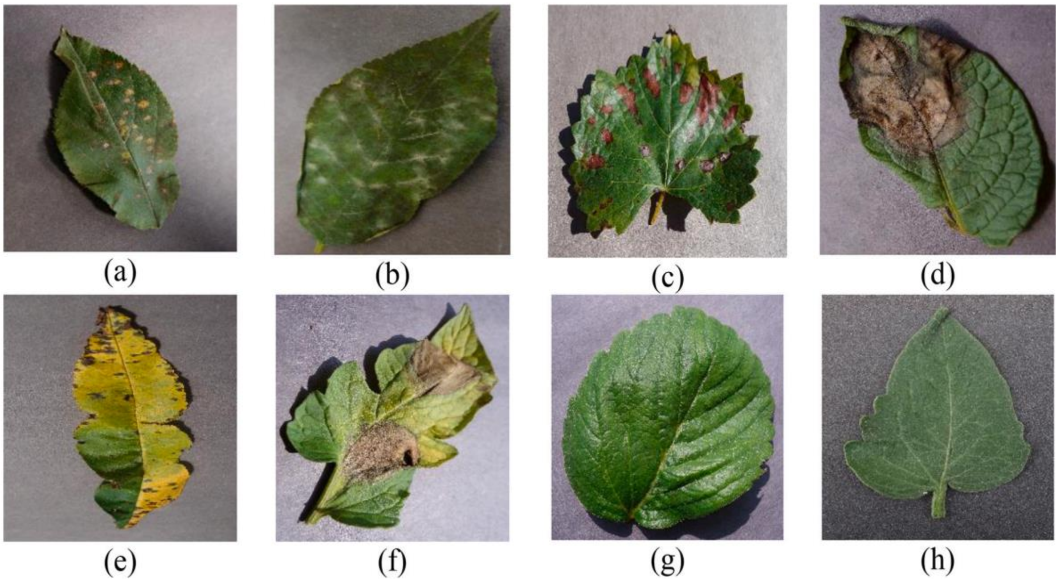
Fig.7. Sample images of Plant Village Dataset [7]

Potential attacks include having malicious content like malware identified as legitimate or controlling vehicle behavior. In the above figure 4 the deep learning model is predicting the digits of the speed limit traffic signal. A non-adversarial image is correctly classified as 10 by the digit classifier. However, we can add a small amount of calculated perturbation to generate an adversarial image. This adversarial image is now getting misclassified by the DNN classifier as 60. In order to generate the calculated perturbation, the adversary uses Direction Sensitivity Estimation. As shown in above Figure 4, the adversary evaluates the sensitivity of the change to each input feature by identifying directions in the data manifold around sample X in which the model F is most sensitive and is likely to result in class change.

Table I. Dataset details: Plant Village

Species	Category	Image Count	Species	Category	Image Count
Apple	Scab	630	Grape	Black rot	1180
Apple	Black rot	621	Grape	Black measles	1383
Apple	Cedar apple rust	275	Grape	Isariopsis leaf spot	1076
Apple	Healthy	1645	Grape	Healthy	423
Cherry	Healthy	854	Orange	Citrus greening	5507
Cherry	Powdery Mildew	1052	Peach	Healthy	360
Corn	Gray Leaf Spot	513	Peach	Bacterial spot	2297
Corn	Common Rust	1192	Pepper	Bacterial spot	997
Corn	Healthy	1162	Pepper	Healthy	1478
Corn	Northern leaf blight	985	Pepper	Early blight	100
Potato	Healthy	152	Raspberry	Healthy	371
Potato	Early Blight	1000	Strawberry	Healthy	456
Potato	Late blight	1000	Strawberry	Leaf scorch	1109
Tomato	Bacterial spot	2127	Tomato	Yellow leaf curl virus	5357
Tomato	Early blight	1000	Tomato	Mosaic virus	373
Tomato	Healthy	1591	Tomato	Target spot	1404

Tomato	Late blight	1909	Tomato	Two spot spider mite	1676
Tomato	Leaf mold	952	Tomato	Blueberry	1502

Apple Dataset - The dataset comprises a total of 3,642 images distributed across four categories. Among these, only 1,822 images are labeled, while the remaining images are unlabeled. The labeled images are specifically chosen to cover categories such as Healthy, Rust, Scab, and multiple diseases. The distribution of images across categories is provided in Table 2. Notably, the images were captured in-field without control over the capturing conditions.

Table. II Apple Dataset description

Category	Image Count
Healthy	516
Rust	533
Scab	592
Multiple disease	91
Total	1821

Maize Dataset - The Maize dataset comprises 400 images distributed across four distinct categories of maize diseases. The total count of images, including those in the test set, is provided in Table 3 for each respective category. Notably, these images were captured under real field conditions, without any background removal. Within each category, 100 images are allocated for training purposes, while a subset of images from each category is set aside for testing.

Table. III Maize Dataset description

Category	Image Count
Eyespot	108
Gross's Bacetrial Wilt	115
Gray Leaf Spot	115
Phaeosphaeria Spot	119
Total	481

Rice Dataset: this dataset, consisting of rice diseases categorized into five groups, was made available by the Fujian Institute of Subtropical Botany, located in Xiamen, China. Each category contains a total of 100 images, resulting in 500 images overall. Additionally, test images are provided with varying numbers of examples. The specific count of images in each category is detailed in Table 4.

Table. IV Rice Dataset description

Category	Image Count
Bacterial Leaf Streak	108
Leaf Scald	115
Leaf Smut	115
Stackburn	107
White Tip	115
Total	560

4.3.Performance Measurement Parameters

The classification performance is evaluated by four parameters, i.e., accuracy, sensitivity, specificity, and F-measure by using confusion matrix. below given table shows the confusion matrix and based on this, other parameters are computed as mentioned in equations (number)

Table.V. Confusion matrix representation

	Positive	Negative	Total
Positive	T_p	F_p	$T_p + F_p$
Negative	F_N	T_N	$F_N + T_N$
Total	$T_P + F_N$	$T_P + T_N$	

The detection accuracy is computed based on the values obtained as mentioned in confusion matrix such as true positive, false positive, false negative, and true positive. The accuracy can be computed as:

$$Accuracy = \frac{T_p + T_N}{T_p + T_N + F_p + F_N} \qquad (9)$$

Similarly, we compute the sensitivity performance with the help of confusion matrix. The sensitivity can be expressed as:

$$Sensitivity = \frac{T_P}{T_P + F_N} \qquad (10)$$

The specificity can be computed as:

$$Specificity = \frac{T_N}{T_N + F_P} \qquad (11)$$

And, F-measure is can be computed as

$$F - measure = \frac{2 \times T_P}{2 \times T_P + F_N + F_P} \qquad (12)$$

4.4.Comparative Analysis

The first phase of this approach is to apply data pre-processing and data augmentation models. Below given figure 7 shows the outcome of this stage. According to this step, we have “Pepper Bell” class affected by “Bacterial Spot” disease.

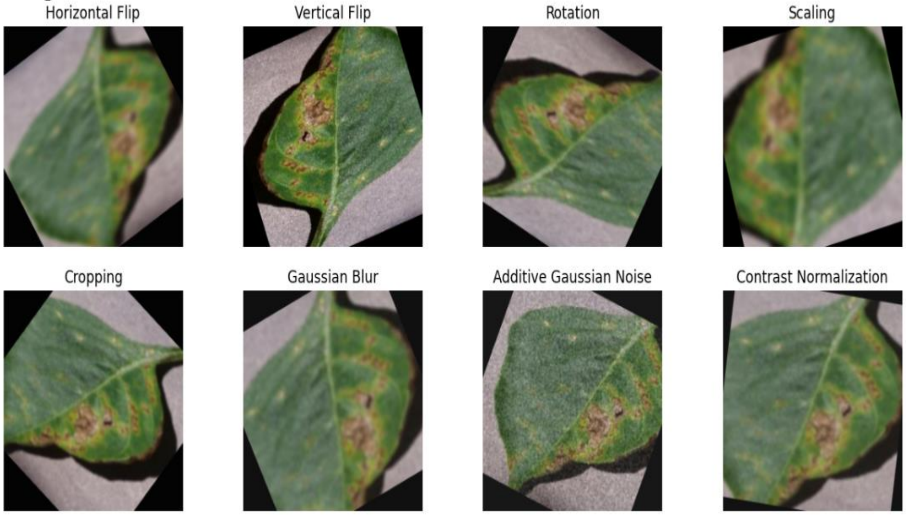

Fig.8. Data augmentation[8].

Further, we apply CNN based feature extraction process on these data where convolution layer, pooling layers and activation functions perform certain operations to obtain the feature set. Below given figure 8 depicts the features corresponding to the activation functions.

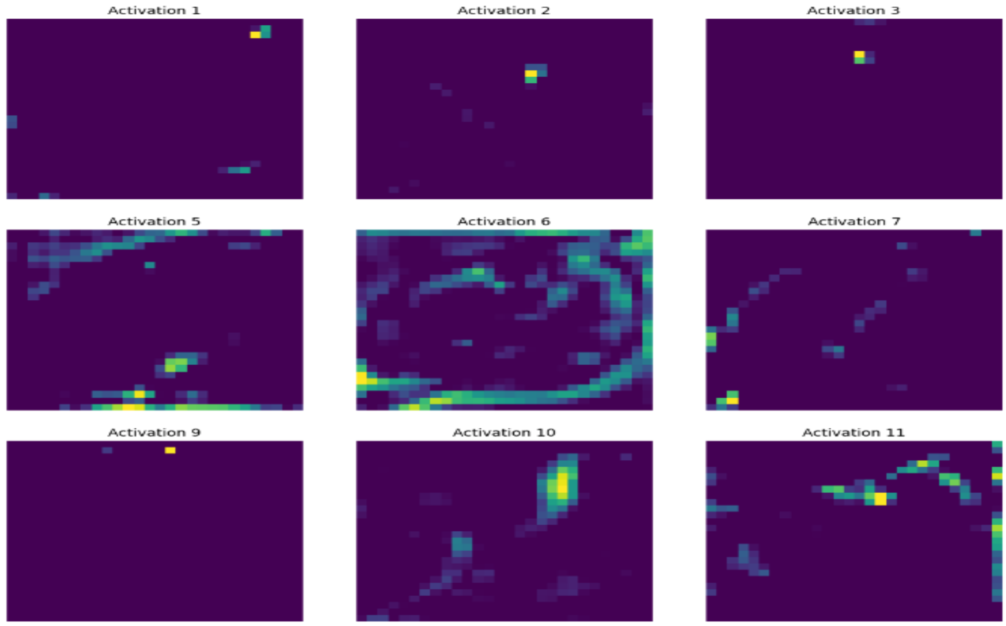

Fig. 9. Outcome of CNN based feature extraction[9].

In next step, we apply proposed ensemble classification approach to classify the leaf type and its corresponding disease. Below given table 6 demonstrates the overall classification performance in terms of loss and accuracy for Plant Village, Apple, Maize and Rice datasets.

Table.VI Comparative analysis with existing methods for different dataset.

Classification Method	Evaluation Parameter	Dataset			
		Plant Village	Apple	Maize	Rice
EfficientNet B0 [24]	Loss	0.2121	2.10	0.399	0.420
	Accuracy	95.69	64.51	85.18	86.67
MobileNet v2 [24]	Loss	0.040	0.652	0.422	0.817
	Accuracy	99.25	81.72	93.82	95.00
ShuffleNet v2 [24]	Loss	0.096	2.62	1.20	1.17
	Accuracy	97.96	41.93	77.78	75.00
GhostNet [24]	Loss	0.169	3.93	2.67	2.32
	Accuracy	96.18	39.78	39.50	43.33
Residual CNN with attention [25]	Loss	0.506	1.01	2.45	0.8945
	Accuracy	92.79	69.31	62.96	80.00
Teacher Student Multitask CNN [26]	Loss	0.1252	0.548	0.961	0.5798
	Accuracy	98.10	89.78	87.13	93.33
Multi-crop CNN [27]	Loss	0.9301	1.165	1.54	0.1057
	Accuracy	91.25	87.10	86.42	95.00
Deep Transfer Learning [28]	Loss	0.105	0.301	1.557	0.2933
	Accuracy	96.82	75.89	80.38	92.00

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

VGG-ICNN [24]	Loss	0.0497	0.0078	0.825	0.0542
	Accuracy	99.16	94.24	91.36	96.67
Proposed Model	Loss	0.085	0.0056	0.251	0.0351
	Accuracy	99.45	96.30	96.85	98.25

The comparative analysis shows that the proposed approach has reported highest classification accuracy as 99.45%, 96.30%, 96.85%, and 98.25% for Plant Village, Apple, Maize, and Rice dataset. EfficientNet B0, despite being more efficient compared to traditional architectures like ResNet or Inception, may still have relatively high computational requirements compared to lighter architectures like MobileNet or ShuffleNet. Moreover, it tends to have higher memory requirements compared other light weight architectures. MobileNetv2 has limited capacity for capturing complex features also its performance is sensitive to hyperparameters and training configurations.

CONLUSION

In this work, we have focused on development of sophisticated deep learning-based approach for plant disease detection and classification. the first phase of this work includes data augmentation methods to address the data imbalance issue and incorporate the diversity in dataset. in next step, Mask RCNN based feature extraction model is presented where the backbone architecture is modified by adding channel attention and upsampling processes. the obtained segmented image is processed through the CNN based feature extraction phase to obtain the final feature set. Finally, SVM, DT and RF classifiers are used to construct the ensemble classifier with the help of majority voting scheme. the experimental analysis shows that proposed approach achieved better classification accuracy and reduced the training loss when compared with the existing schemes.

REFERENCES

1. “The state of food security and nutrition in the world (2023).” FAO; IFAD; UNICEF; WFP; WHO.
2. T.D.March(2022),“StateofagricultureinIndia,”Prsindia.org.[Online].Available:https://prsindia.org/files/policy/policy_analytical_reports/State%20of%20Agriculture%20in%20India.pdf Ceron.
3. Mukti, I.Z.; Biswas, D(2019). “Transfer Learning Based Plant Diseases Detection Using ResNet50”. In Proceedings of the 2019 4th International Conference on Electrical Information and Communication Technology (EICT), Khulna, Bangladesh, 20–22 December 2019.
4. Arunnehru, J.; Vidhyasagar, B.S.; Anwar Basha, H. (2020). “Plant Leaf Diseases Recognition Using Convolutional Neural Network and Transfer Learning”. In International Conference on Communication, Computing and Electronics Systems; Bindhu, V., Chen, J.,Tavares, J.M.R.S., Eds.; Springer: Singapore, 2020; pp. 221–229.
5. S. Verma, A. Chug, and A. P. Singh (2018), “Prediction models for identification and diagnosis of tomato plant diseases,” in 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2018.
6. Singh, V., Sharma, N., & Singh, S. (2020). A review of imaging techniques for plant disease detection. Artificial Intelligence in Agriculture, 4, 229-242.

7. Liu, G. (2021, November). An Image Combination Segmentation Method Based on Clustering Analysis and Edge Detection. In 2021 4th International Conference on Digital Medicine and Image Processing (pp. 30-34).

8. Shrivastava, V. K., & Pradhan, M. K. (2021). Rice plant disease classification using color features: a machine learning paradigm. Journal of Plant Pathology, 103(1), 17-26.

9. Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms.

10. Basavaiah, J., & Arlene Anthony, A. (2020). Tomato leaf disease classification using multiple feature extraction techniques. Wireless Personal Communications, 115(1), 633-651.

11. Upadhyay, S. K., & Kumar, A. (2022). A novel approach for rice plant diseases classification with deep convolutional neural network. International Journal of Information Technology, 14(1), 185-199.

12. A Kamilaris and F. X. Prenafeta-Boldú (2018), "Deep learning in agriculture: A survey", Comput. Electron. Agricult., vol. 147, pp. 70-90.

13. G. L. Grinblat, L. C. Uzal, M. G. Larese and P. M. Granitto, (2016) "Deep learning for plant identification using vein morphological patterns", Comput. Electron. Agricult., vol. 127, pp. 418-424.

14. S. P. Mohanty, D. P. Hughes and M. Salathé(2016), "Using deep learning for image-based plant disease detection", Frontiers Plant Sci., vol. 7, pp. 1419.

15. J. Ma, K. Du, F. Zheng, L. Zhang, Z. Gong and Z. Sun (2018), "A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network", Comput. Electron. Agricult., vol. 154, pp. 18-24, Nov.

16. Y. Kawasaki, H. Uga, S. Kagiwada and H. Iyatom i(2015), "Basic study of automated diagnosis of viral plant diseases using convolutional neural networks", Proc. Int. Symp. Vis. Comput., pp. 638-645

17. Guo, Y., Zhang, J., Yin, C., Hu, X., Zou, Y., Xue, Z., & Wang, W. (2020). Plant disease identification based on deep learning algorithm in smart farming. Discrete Dynamics in Nature and Society, 2020, 1-11.

18. Saleem, M. H., Khanchi, S., Potgieter, J., & Arif, K. M. (2020). Image-based plant disease identification by deep learning meta- architectures. Plants, 9(11), 1451.

19. Roy, A. M., & Bhaduri, J. (2021). A deep learning enabled multi-class plant disease detection model based on computer vision. Ai, 2(3), 413-428.

20. Chug, A., Bhatia, A., Singh, A. P., & Singh, D. (2023). A novel framework for image-based plant disease detection using hybrid deep learning approach. Soft Computing, 27(18), 13613-13638.

21. Bhagat, S., Kokare, M., Haswani, V., Hambarde, P., & Kamble, R. (2022). Eff-UNet++: A novel architecture for plant leaf segmentation and counting. Ecological Informatics, 68, 101583.

22. Yang, K., Zhong, W., & Li, F. (2020). Leaf segmentation and classification with a complicated background

using deep learning. Agronomy, 10(11), 1721.

23. Yang, X., Chen, A., Zhou, G., Wang, J., Chen, W., Gao, Y., & Jiang, R. (2020). Instance segmentation and classification method for plant leaf images based on ISC-MRCNN and APS-DCCNN. IEEE Access, 8, 151555-151573.

24. Thakur, P. S., Sheorey, T., & Ojha, A. (2023). VGG-ICNN: A Lightweight CNN model for crop disease identification. Multimedia Tools and Applications, 82(1), 497-520.

25. K. Ramamurthy, H. M., S. Anand, P. M. Mathialagan, A. Johnson, M. R. (2020), "Attention embedded residual CNN for disease detection in tomato leaves", Applied Soft Computing 86.

26. M. Brahimi, S. Mahmoudi, K. Boukhalfa, A. Moussaoui, (2019) "Deep interpretable architecture for plant diseases classification", in: 2019 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA), IEEE, 2019, pp. 111–116

27. A. Picon, M. Seitz, A. Alvarez-Gila, P. Mohnke, A. OrtizBarredo, J. Echazarra, (2019) "Crop conditional convolutional neural networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions", Computers and Electronics in Agriculture 167 105093.

28. J. Chen, J. Chen, D. Zhang, Y. Sun, Y. A. Nanehkaran, (2020) "Using deep transfer learning for image-based plant disease identification", Computers and Electronics in Agriculture 173 105393.