Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

LEAFHEALTHAI: AN ROI-OPTIMIZED DEEP LEARNING FRAMEWORK FOR ENHANCED LEAF DISEASE DETECTION IN PRECISION AGRICULTURE

B. SUREKHA[1*] AND DR. T. SUBHAMASTHAN RAO[2]

[1]Department of Computer Science and Engineering Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India.

[2]Department of Computer Science and Engineering Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India.

surekhareddygujja@gmail.com, subhamasthanrao@kluniversity.in

ABSTRACT

Early and accurate detection of plant leaf diseases is essential for improving crop yield and ensuring sustainable agricultural practices. Traditional Convolutional Neural Network (CNN) models often process entire leaf images without emphasizing disease-affected regions, leading to misclassifications, poor interpretability, and reduced performance under real-world conditions. This study introduces LeafHealthAI, a novel deep learning framework integrating Grad-CAM-based Region of Interest (ROI) attention with a weighted categorical cross-entropy loss to enhance precision in disease localization and classification. The proposed LDDNet-WROI model leverages ROI-guided learning to focus on disease-relevant features while dynamically addressing class imbalance. Experiments conducted on the benchmark PlantVillage dataset, comprising 54,000 images across 38 disease classes, demonstrate that LeafHealthAI achieves a classification accuracy of 98.46%, surpassing baseline models such as VGG16, ResNet50, and EfficientNetB0. Visualization using Grad-CAM heatmaps confirms the framework's interpretability by clearly highlighting disease-affected areas. The results validate that ROI-driven attention and weighted optimization significantly improve model robustness, making LeafHealthAI suitable for real-time precision agriculture applications and scalable deployment in IoT-enabled crop monitoring systems.

Keywords - *Plant Disease Detection, Deep Learning, Region of Interest, Weighted Loss, Precision Agriculture*

1. INTRODUCTION

Plant diseases are a serious challenge to global agricultural productivity, particularly in crops such as tomato, potato, and corn, where early and accurate detection is crucial for preventing yield losses and ensuring sustainable farming practices. Precision agriculture is an emerging approach that leverages advanced technologies like sensors, IoT-enabled monitoring, and AI-driven analytics to optimize crop management and resource utilization [2]. Within this context, deep learning-based image analysis has emerged as a powerful tool for automating plant disease detection, reducing the dependency on manual inspection, which is often time-consuming and prone to human error.

Traditional Convolutional Neural Network (CNN) models have demonstrated high accuracy in plant disease classification on curated datasets like PlantVillage. However, most conventional CNN approaches process entire leaf images, treating both healthy and background regions equally. This often results in reduced model performance, misclassifications, and limited interpretability, especially under real-world conditions with noisy, cluttered, or occluded data [3]. To address these limitations, our study introduces the concept of Region of Interest (ROI), which represents specific portions of an image containing critical features—such as disease-affected areas of a leaf—while ignoring irrelevant background information. The ROI in our framework is generated using Gradient-

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

weighted Class Activation Mapping (Grad-CAM), a visualization method that produces heatmaps highlighting image regions most influential in the model's decision-making process [4]. Furthermore, to manage class imbalance and improve learning from disease-prone regions, we employ a Weighted Loss Function, which assigns higher penalties to misclassified disease areas while reducing the influence of less important background pixels [5].

Recent literature highlights a critical gap: the lack of spatial attention to disease-affected areas and inadequate interpretability in deep models. Additionally, existing methods often ignore class imbalance and environmental variability, which is standard in practical farming scenarios. These limitations emphasize the need for a more focused and intelligent learning framework. To address these challenges, the present study proposes a Region of Interest (ROI)-optimized deep learning framework named LDDNet-WROI, which enhances conventional CNN performance by integrating ROI attention and weighted categorical loss. The main objective is to improve disease classification accuracy by guiding the network to concentrate on the most relevant regions of the leaf image while compensating for the varying class distributions through dynamic loss weighting.

The proposed research introduces several novelties: (i) utilization of Grad-CAM to generate class-specific ROI heatmaps; (ii) generation of binary ROI masks that are integrated into the feature learning process; (iii) formulation of a custom weighted loss function that emphasizes disease-relevant regions; and (iv) enhancement of the base LDDNet architecture to form LDDNet-WROI, capable of delivering interpretable and robust predictions. The research contributions also include extensive evaluation using the PlantVillage dataset, comparative analysis with existing models, and an ablation study to isolate the impact of each innovation.

The remainder of the paper is structured as follows. Section 2 provides a comprehensive literature review, analyzing key deep learning approaches for plant disease detection. Section 3 presents the proposed methodology, detailing the architecture of LDDNet-WROI, the ROI extraction process, and the training configuration. Section 4 discusses the experimental setup, performance metrics, and visualization results. Section 5 offers an in-depth discussion, interprets the results, and outlines the study's limitations. Finally, Section 6 concludes the paper and outlines directions for future research, including deployment possibilities in real-world innovative farming applications and integration of multi-modal data sources.

2. RELATED WORK

This section reviews recent advancements in deep learning models for plant leaf disease detection across various crops and diagnostic approaches. Ritharson et al. [1] presented a deep learning-based bespoke VGG16 model that can accurately detect 99.94% of rice leaf illnesses. Dependency on massive datasets and possible overfitting are drawbacks. The model will be extended to additional crops, and instruments for diagnosing diseases will be improved for wider agricultural use. Bouacida et al. [2] improved generalization; however, the deep learning model must be more resilient and adaptable. It diagnoses plant illnesses with 97.13% accuracy. Simhadri et al. [3] examined deep learning techniques for detecting rice leaf disease, pointing out shortcomings in current models and recommending further advancements. Rashid et al. [4] demonstrated MMF-Net, a CNN-based model that can identify maize leaf diseases with 99.23% accuracy. Data processing and complexity are two limitations. Future research will focus on digesting various environmental data and enhancing model flexibility. Alaa et al. [5] presented a 98.80% accurate feature extraction technique for tomato leaf disease detection that uses conformable polynomials. One of the limitations is dataset reliance. Subsequent research endeavors will refine feature extraction methodologies and broaden the model's relevance to diverse crops.

Polly and Devi [6] created a deep learning-based system with 99% damage detection and 97% classification accuracy for plant leaf disease diagnosis. The following study attempts to increase the system's versatility and broaden its use to include more crops. Umar et al. [7] created a 98.8% accurate improved YOLOv7 model to identify seven tomato leaf diseases. Constraints on the dataset are examples of limitations. The improvement of adaptation to diverse field circumstances and illnesses will be the main focus of future studies. Sujatha et al. [8] compared and found that DL approaches are superior to ML methods for identifying citrus plant diseases. In

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

future studies, fuzzy logic and bio-inspired approaches will improve accuracy with fewer datasets. Zhang et al. [9] used ResNet101 and k-means clustering to improve Faster RCNN for identifying tomato leaf diseases. Single-leaf detection is one of the limitations. The following study intends to incorporate photos of actual plants and other disease traits for increased accuracy. Khan et al. [10] suggested a quick and highly accurate approach for detecting cucumber leaf disease. Among the limitations are difficulties with segmentation and feature extraction. These techniques will be refined in the future for better detection and categorization.

Algani et al. [11] presented ACO-CNN, a very accurate method for detecting plant leaf diseases. Time and skill needs are two constraints. Techniques will be refined in future work for increased efficacy and efficiency. Ahmad et al. [12] examined 70 deep learning studies on the detection of plant diseases, pointed out knowledge gaps, and recommended the creation of new tools to increase precision and control. Panchal et al. [13] achieved 93.5% accuracy in classifying agricultural diseases using deep learning. Future research aims to enhance data collection and integrate recommended treatments. Moupojou et al. [14] presented FieldPlant, a dataset including 5,170 field photos annotated by experts that enhances PlantDoc's plant disease categorization. Upcoming projects will involve using picture segmentation and improving models. Shovon et al. [15] presented PlantDet, a deep ensemble model that improves earlier techniques for classifying betel leaf disease and rice disease. Future research will examine more datasets, better explainability, and optimization strategies.

Kotwal et al. [16] examined the transition of plant disease diagnosis from conventional to deep learning methods, pointing out accuracy and data shortages. Upcoming projects will enhance illness severity recognition, dataset variety, and model efficacy. Shewale and Daruwala [17] enhanced accuracy and efficiency over manual approaches for diagnosing tomato leaf disease by utilizing deep learning. Extending datasets and improving the model are tasks for the future. Nikith et al. [18] identified CNN as the most accurate model at 96% when comparing SVM, KNN, and CNN models for leaf disease identification. Expanding the dataset will be a future project that might increase SVM and KNN accuracy. Ahmad et al. [19] evaluated the extension of DL models for identifying corn disease using different datasets. Future research needs to incorporate various environmental factors and further enhance generalization. Datta and Gupta [20] created a Deep CNN with potential IoT integration to accurately classify tea leaf diseases, with 96.56% accuracy.

Dahiya et al. [21] used the PlantVillage dataset, researchers compared deep learning architectures for identifying plant diseases and found that ResNet50 and ResNet101 performed better. Umamageswari et al. [22] created software with 98.43% accuracy on Kaggle data for real-time leaf disease diagnosis using FCM, SIFT, and LSTM. Jackulin and Murugavalli [23] examined and contrasted deep learning and machine learning techniques for identifying plant diseases, emphasizing the superiority of deep learning. Rao et al. [24] deployed AlexNet on an app and achieved 99% and 89% accuracy in classifying illnesses of grape and mango leaves, respectively. Zhong and Zhao [25] achieved an accuracy of 93.51% to 93.71% while using DenseNet-121 to suggest apple leaf disease diagnosis techniques.

Noon et al. [26] examined 45 deep learning methods for determining plant leaf stress, emphasizing difficulties and accuracy gains. Tiwari et al. [27] created and thoroughly tested a deep learning model for plant disease detection with a high % accuracy rate of 99.2% and quick processing. Yadav et al. [28] created a CNN-based model with a 98.75% accuracy rate in identifying peach leaf bacteriosis, meaning that UAV integration and multi-disease detection might be possible. Li et al. [29] emphasized the use of deep learning in plant disease diagnosis while pointing out the requirement for real-condition data and issues with dataset stability. Atila et al. [30] examined how well Efficient Net performs compared to other deep learning models for categorizing plant diseases, adding that future work will increase datasets and implement models for mobile use.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: Comparative Summary of Deep Learning-Based Approaches for Plant Leaf Disease Detection

Ref	Approach	Technique	Algorithm	Dataset	Limitation / Future Scope
[1]	Deep Learning	CNN	R-CNN	Custom dataset	Extend VGG16 to other crop diseases; develop more effective diagnostic tools.
[3]	Deep Learning	CNN	Improved Backtracking Search (IBS)	Kaggle dataset	Develop adaptable systems suited for actual field conditions.
[5]	Deep Learning	AI techniques	KNN, SVM	PlantVillage	Study multi-infection types for improved practical application.
[13]	Deep Learning	CNN	DL algorithms	PlantVillage	Collect disease data across stages using multi-sensors; integrate cure suggestions and outcome validation.
[14]	Deep + Machine Learning	SVM + Feature Extraction	Xception	PlantDoc	Apply optimization to mitigate overfitting; explore additional datasets for early diagnosis.
[24]	Deep Learning	CNN	SGDM	PlantVillage	Expand classification to more disease classes; develop a farmer-oriented recommendation system.
[27]	Deep + Machine Learning	ML + DL techniques	DL algorithms	Custom dataset	Expand the dataset with more diverse leaf images for robust field deployment.
[28]	Deep + Machine Learning	Augmentation	DL + ML algorithms	PlantVillage	Train on varied leaf disease images to support multi-disease detection in peach crops.
[30]	Deep Learning	CNN	LAB-based hybrid segmentation	PlantVillage	Increase plant diversity and the number of classes in future datasets.
[31]	Deep Learning	Deep CNN	Back-propagation	ImageNet	Extend the model to assess disease severity and apply transfer learning to other crops.

Thangaraj et al. [31] created a model for detecting tomato leaf disease using transfer learning and discovered that the Adam optimizer produces the best results. In the future, the model will be applied to different plants, and the severity of the illness will be evaluated. Ngugi et al. [32] discussed deep learning and image processing for diagnosing plant diseases, highlighting excellent accuracy but inconsistent results across datasets. Future research should tackle real-world deployment issues. Abed et al. [33] suggested a deep learning system that achieves excellent accuracy for early bean disease detection utilizing U-Net and several CNN models. Further research may enhance robustness under various circumstances. Lakshmi and Savarimuthu [34] presented an improved version of the EfficientDet model that offers 74.10% mAP and efficient

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

performance on low-end hardware to detect plant diseases. Future research may examine more practical applications and optimization. Hu et al. [35] improved deep learning to analyze the severity and detection of tea leaf blight, increasing accuracy but requiring more extensive tissue coverage.

Table 2: Mapping of Public and Custom Datasets Used in Deep Learning-Based Plant Leaf Disease Detection Studies

Dataset	References
Custom dataset	[1], [11], [27]
PlantVillage dataset	[2], [4], [5], [6], [7], [12], [13], [15], [17], [19], [21], [24], [26], [28], [29], [30], [32], [33], [36]
Rice Leaf Dataset (Kaggle)	[3]
AI Challenger 2018 (https://challenger.ai/competition/pdr2018)	[9], [37]
PlantDoc dataset	[14]
ImageNet dataset	[16], [29], [31], [35]
Soybean dataset	[18]
CD&S dataset	[19]
Kaggle dataset	[20], [22]
DeepWeeds dataset	[33]
COCO image dataset	[34]
Image Database (unspecified)	[39]
LWDCD2020 dataset	[40]

Sachdeva et al. [36] suggested a Bayesian-enhanced DCNN with 98.9% accuracy for plant disease identification; nevertheless, other illnesses need to be investigated in future research. Zhou et al. [37] showed a reorganized residual dense network with the possibility for more improvement that can detect tomato leaf disease with 95% accuracy. Divakar et al. [38] used SMOTE and an ensemble algorithm to detect plant leaf disease and eliminate incorrect predictions; EfficientNetB7 is shown to be the best solution. Jiang et al. [39] enhanced VGG16 for multi-task learning in leaf disease detection, attaining excellent accuracy for illnesses of wheat and rice. Goyal et al. [40] described a unique deep learning model with higher accuracy that outperforms VGG16 and RESNET50 in classifying wheat illnesses. Table 1 compares deep learning-based leaf disease detection approaches, outlining techniques, algorithms, datasets, and limitations, focusing on accuracy, adaptability, and future improvements. Table 2 lists datasets used in reviewed studies, highlighting PlantVillage's dominance and the role of custom and benchmark datasets in training deep learning models effectively. Recent studies demonstrate the effectiveness of deep learning models like VGG16, ResNet, and EfficientNet in detecting leaf diseases with high accuracy. Despite their success, dataset dependency, generalizability, and real-world deployment persist. Future directions focus on dataset diversification, environmental adaptability, severity analysis, and practical agricultural integration. 42–50. Literature explores AI in healthcare, agriculture, and smart grids, focusing on deep vein thrombosis diagnosis, irrigation, disease classification, and electric vehicle

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

charging. Techniques include ensemble learning, heuristic strategies, and bio-inspired optimization, enhancing efficiency, predictive accuracy, and intelligent decision-making across domains.

3. PROPOSED FRAMEWORK

One such follow-up of this research is the production of LeafHealthAI, a novel, ROI-optimised deep learning model that transforms such detections into attacks of plant leaf disease. It combines Grad-CAM-based region localization with a weighted loss adjustment approach to emphasize diseased regions. Based on the LDDNet architecture, the framework achieves high accuracy while being interpretable and robust, which is suitable for deployment in real-world agricultural monitoring systems.

3.1 System Overview: LeafHealthAI

Herein, we present LeafHealthAI, a novel AI-based framework (as depicted in Figure 1) that addresses the issues of accuracy and robustness in identifying leaf diseases in crops. Leveraging the publicly available LDDNet model, the system enhances the model by incorporating the Weight-Based Region of Interest (ROI) Optimization strategy, leading to the improved model known as LDDNet-WROI. Conventional profound learning algorithms master entire leaf images without focusing on the affected part, which decreases the system's efficiency, especially in complex backgrounds or variable environmental conditions. The ROI-guided approach proposed here learns to leverage disease-relevant sections of the leaf images while rejecting irrelevant background information to overcome these limitations.

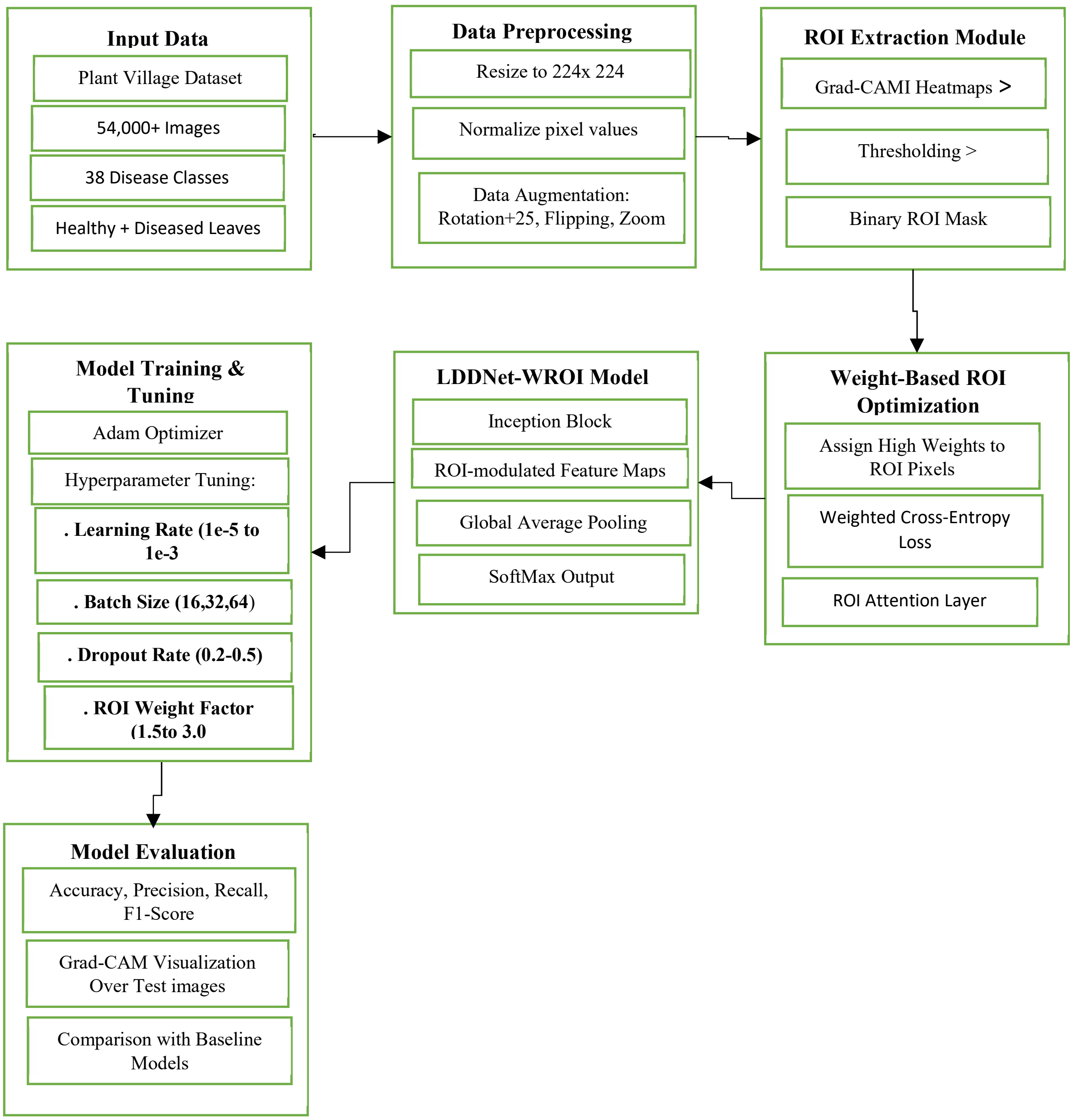

Figure 1: Overall Architecture Of The Proposed Leafhealthai System For ROI-Optimized Leaf Disease Detection In Precision Agriculture

LeafHealthAI is built on three core components. The ROI Extraction Module generates heatmaps that highlight the areas affected by the disease in each leaf image using Gradient-weighted Class Activation Mapping (Grad-CAM) [53]. They are processed to get the ROI mask through thresholding, which helps identify important regions of interest for classification. The Weight-Based ROI Optimization strategy is proposed to apply a weighted loss function in the training process to exploit the detected ROI better. It increases the weights for the disease-related areas, allowing the model to learn the discriminant features in these regions, which improves classification performance. LDDNet-WROI: Enhanced Deep Learning Model — ROI-based attention mechanisms and a weighted categorical cross-entropy loss enhance the original LDDNet architecture. First, the attention mechanism in the feature maps ensures that the features in the ROI

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

regions are more emphasized. Then the weighted loss heavily penalizes misclassification in these important critical regions. In summary, LeafHealthAI can provide high-accuracy, reliable leaf disease detection, enabling early intervention and effective crop management in precision agriculture.

3.2 Dataset Preparation

3.4.1. PlantVillage dataset. The dataset for developing and evaluating the proposed LeafHealthAI system is the PlantVillage dataset [41]. This data is commonly used in agriculture due to its completeness, quality, and variety. The images include over 54k high-resolution images of healthy and diseased leaves, 14 crop species, and 38 classes. Electric images in the dataset are accurately labeled, representing various diseases or healthy leaf conditions, thereby making it highly suitable for supervised learning tasks.

Before any dataset can be used to train any model, data cleaning is performed so that all datasets are consistent and reliable. This means filtering out duplicate photos, poor-quality samples, and any ambiguous/ corrupt entries. Moreover, to ensure uniformity among all input samples, the image formats and resolutions are standardized. Preprocessing the data helps clean up noise and create a dataset from which the model can learn.

The dataset is split into training and testing data for model training and evaluation. Notably, 80% of the images are used for model training, and 20% are used for validation and testing. The split is followed in a stratified fashion so that all classes of the disease are represented in proportion in both subsets to maintain the class balance.

There are multiple reasons for choosing the PlantVillage dataset. Its large diversity of crop species and disease types provides a good testing ground for whether the proposed framework is generalizable. The dataset is also well-labeled and balanced, making it suitable for effective supervised deep learning models. The high-dimensional aspect of the images also allows the use of ROI-extraction techniques, which is a core part of the LeafHealthAI system. The framework is comprehensively trained and tested based on the PlantVillage data set for practical transfer of the framework to real agricultural precision agriculture. Notations in the proposed system are described in Table 3.

Table 3: Notations Used In Leafhealthai System

Notation	Description
D	Input dataset (PlantVillage dataset)
D_{aug}	Augmented dataset after preprocessing
D_{train}, D_{test}	Training and testing subsets of D_{aug}
I	Input leaf image
I_{aug}	Augmented image obtained after applying transformations
A^k	Feature map output from the k^{th} channel of the last convolutional layer
$\frac{\partial y^c}{\partial A^k}$	Gradient of predicted class score y^c w.r.t feature map A^k
α_k^c	Weight for feature map A^k in Grad-CAM
$L^c_{\text{Grad-CAM}}$	Grad-CAM heatmap for class c
ROI(i, j)	ROI mask value at pixel location (i, j), 1 for ROI region, 0 otherwise

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$F_{i,j,k}$	Feature map value at location (i, j), channel k
$F'_{i,j,k}$	ROI-modulated feature map value at location (i, j), channel k
$W_{i,j}$	Weight assigned to pixel at (i, j) based on ROI
λ_{ROI}	Weight assigned to ROI regions
λ_{BG}	Weight assigned to background regions
η	Learning rate
B	Batch size
D	Dropout rate
N	Total number of test samples
N_{correct}	Number of correctly classified test samples
Z	Total number of pixels in the feature map

3.3 Preprocessing Stage

LeafHealthAI leverages the importance of preprocessing, looking into the input data, and getting ready to learn efficiently. This process includes multiple transformations performed on the raw images to maintain consistency, enhance the visibility of features, and augment the dataset to achieve better model generalization. For consistency, all images input from the PlantVillage dataset are resized to a standard of 224 × 224 pixels. This reduces the leaf images to an appropriate size for the input layer of the LDDNet-WROI model using the minimum amount of data required to maintain key leaf features.

Normalization is then performed to bring pixel intensity values into the range of [0, 1]. It speeds up convergence model training by removing the influence of pixel ranges. Mathematically, we normalize each pixel value in an image as in Eq. 1.

$$p_{norm} = \frac{p - p_{min}}{p_{max} - p_{min}} \quad (1)$$

where p_{min} and p_{max} are the minimum and maximum pixel intensity values. Data augmentation techniques are also applied to enhance the model's rigidity and avoid overfitting.

Random transformations are performed on each training image, including horizontal flipping, rotation within a range of ±25 degrees, random zooming up to 20%, and brightness. Let I be the original image and T The transformation function, the augmented image I_{aug} is written as in Eq. 2.

$$I_{aug} = T(I) \quad (2)$$

where T is composed of a combination of rotation R(θ), flipping F, zooming Z(s), and brightness adjustment B(β) functions. This augmentation strategy ensures that the model is trained on images that misbehave, in a realistic sense.

Last but not least, if the images do not come in RGB mode, we convert them, making sure the input channels are consistent across datasets. The images that we end up preprocessing are what go into the next steps of ROI Extraction and Model training. In this way, the preprocessing pipeline guarantees that the dataset is clean, diverse, and formatted correctly for the best performance of the LeafHealthAI system.

3.4 ROI Extraction Process

ROI Extraction: The ROI extraction is one of the most critical steps in the LeafHealthAI

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

architecture. It removes all information from the image except for the disease-affected area. This allows the model to focus on the most relevant regions rather than processing the entire image equally, thus improving classification accuracy and efficiency.

This is done using Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM uses the target class's gradients flowing into the model's last convolutional layer to generate a localization heatmap, highlighting the important areas that affect the class decision of the model. Given an input image, the feature maps extracted from the final convolutional layer are denoted as A^k, and the gradients of the predicted class score y^c w.r.t. A^k are denoted as $\frac{\partial y^c}{\partial A^k}$. The importance weight for each feature map is calculated as in Eq. 3.

$$\alpha_k^c = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \quad (3)$$

where X, and Z indicates the number of pixels in the feature map, and i and j Index the spatial dimensions. We can use this information to generate a heatmap with Grad-CAM. $L_{\text{Grad-CAM}}^c$, which is the weighted combination of the feature maps as in Eq. 4.

$$L_{\text{Grad-CAM}}^c = ReLU\left(\sum_k \alpha_k^c A^k\right) \quad (4)$$

This is ensured by using the ReLU activation, which allows heatmaps to show only positively affecting areas. These heatmaps are then normalized, thresholded, and cropped, producing binary ROI masks. An empirically chosen threshold τ yields the following thresholding measure as in Eq. 5.

$$\text{ROI(i, j)}=\begin{cases} 1, & if\, L_{\text{Grad-CAM}}^c(i,j) \geq \tau \\ 0, & Otherise \end{cases} \quad (5)$$

(where $ROI(i,j)$ is 1 if the pixel at location (i,j) belongs to the ROI). Afterward, these binary ROI masks are used in the next steps to apply local learning. In particular, the ROI masks play a guiding role in both attention mechanisms in the improved version of the LDDNet-WROI model and the weighted loss function, which not only provides rewards to the disease-affected areas of images but also reduces the interference of the background area on the model.

3.5 Weight-Based ROI Optimization Strategy

A Weight-Based Region of Interest (ROI) Optimization strategy is proposed to further improve LeafHealthAI's classification performance. We refer to the optimization technique that refines the model to emphasize the delineated disease-relevant areas during training, while the ROI extraction process identifies these areas from leaf images.

The overall concept is to adapt the conventional categorical cross-entropy loss function, as seen in the typical segmentation methods, by adding a new term calculated from the Region of Interest (ROI) masks. The Grad-CAM process outputs a Region of Interest (ROI) mask for each input image, where higher weights correspond to disease-affected regions and lower weights correspond to background regions, thus making the heatmap ascertainable. (4)and let $w_{i,j}$ denote the weight assigned to the pixel in position (i,j) of the image as in Eq. 6.

$$w_{i,j} = \begin{cases} \lambda_{ROI}, & if ROI(i,j)=1 \\ \lambda_{BG,} if ROI(i,j) = 0 \end{cases} \quad (6)$$

Where λ_{ROI} is the weight applied to ROI regions and $\lambda_{BG,}$ is the weight applied to the background. Generally, $\lambda_{ROI,} > \lambda_{BG,}$ to augment the ROI. Cross Entropy Loss with Equal Representation for all a Image having C classes as in Eq. 7.

$$\text{L}=-\sum_{i-1}^{H}\sum_{j-1}^{W} w_{i,j} \sum_{c-1}^{C} y_{i,j}^{(c)} \log\left(\hat{y}_{i,j}^{(c)}\right) \quad (7)$$

Here, H and W stand for the height and the width of the image, $y_{i,j}^{(c)}$ is the ground truth label for class c at (i,j) and $\hat{y}_{i,j}^{(c)}$ is the predicted probability for class c at the same position. Besides changing the loss function, an attention mechanism is also introduced in the LDDNet-WROI model to further exploit the ROI information. An attention module leverages the ROI masks to modulate the feature maps such that features originating from disease manifesting areas receive a more significant emphasis when the network is trained.

By using a weight substantially greater than or equal to other labels for training, this method effectively guides the model to learn and adapt to the features of input that correlate most strongly with the presence of disease. This, in turn, enhances the accuracy, precision, and robustness of the leaf disease classification process,

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

especially in the presence of diverse elements such as background interference and environmental fluctuations.

3.6 Enhanced Deep Learning Model – LDDNet-WROI

The foundation of the LeafHealthAI framework is an improved deep learning model called LDDNet-WROI (shown in Figure 2). This model expands upon an earlier LDDNet architecture by incorporating Region of Interest (ROI) information. This integration aims to allow the model to pay greater attention to the regions of diseases that are affected, thus increasing its classification precision and interpretability.

The core of the LDDNet architecture is a sequence of convolutional processes extended by an inception-type block of custom designs that achieves multi-scale feature extraction. This block enables the model to learn fine-grained and coarse-grained details that are critical to accurately detecting diseases for a diverse range of leaf types and states.

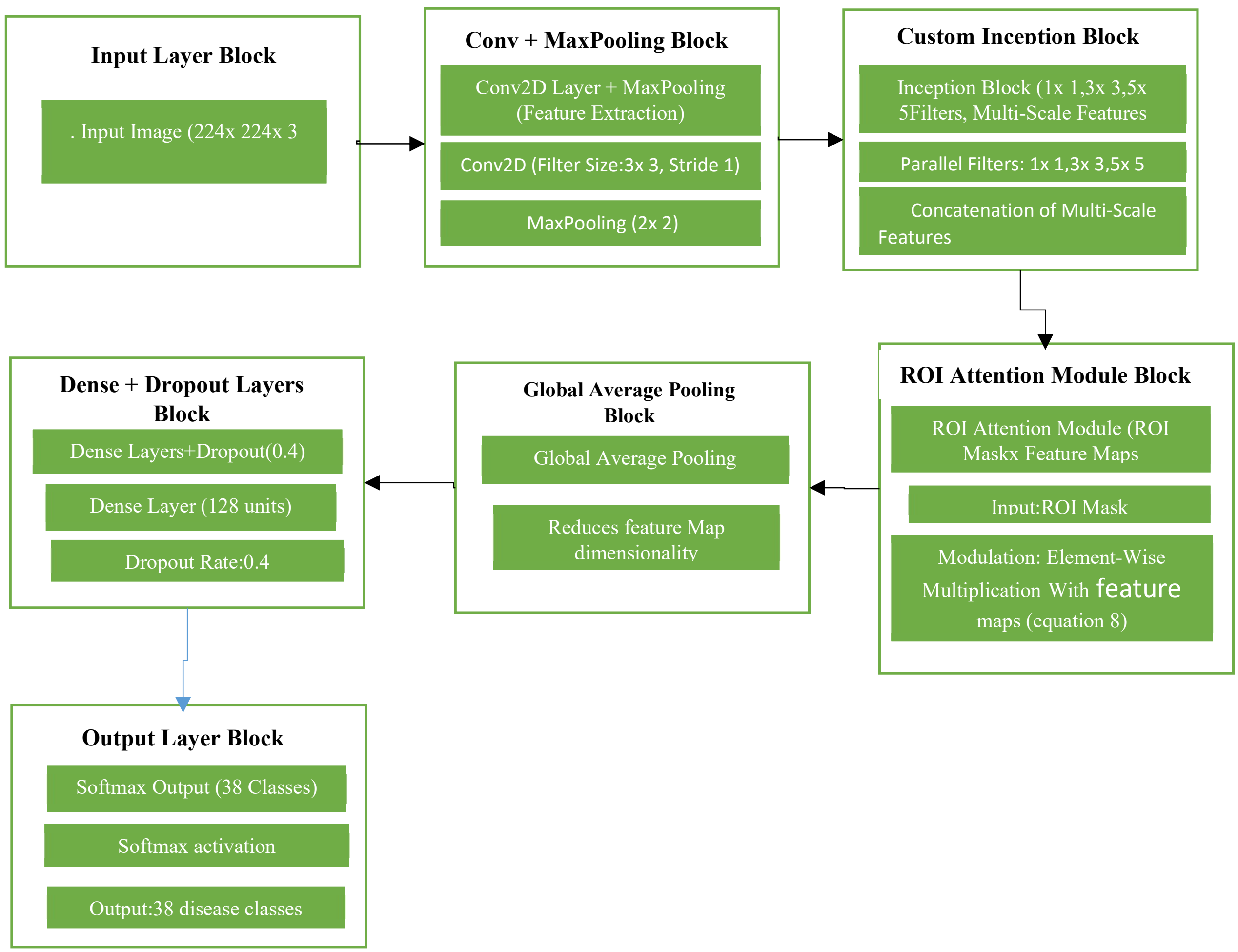

Figure 2: Architecture of the Enhanced LDDNet-WROI Model with ROI Attention and Weighted Loss for Leaf Disease Classification

The proposed LDDNet-WROI realizes ROI optimization via two modifications. To begin with, the addition of the ROI Attention Module after the Inception block. The ROI masks generated in the preprocessing stage are used to modulate the feature maps in this module, which helps to enhance the feature representation of disease-affected regions and reduces the contribution of irrelevant background regions. In mathematical terms, denoting $F_{i,j,k}$ the feature map output at spatial location (i,j) and channel k as, the ROI-modulated feature map $F'_{i,j,k}$ is calculated as in Eq. 8.

$$F'_{i,j,k} = ROI(i,j) \times F_{i,j,k} \quad (8)$$

where $ROI(i,j)$ represents the value of the corresponding ROI mask (1 if the size is in the disease region, 0 otherwise). Second, the model enters training on the Weighted Categorical Cross-Entropy Loss function outlined previously, which highlights correct classification in areas of ROI. This loss function is combined with the attention mechanism to the learning process further, where more significant penalties are applied to misclassifications within the disease-affected regions.

The final LDDNet-WROI layers are a global average pooling layer, followed by fully connected layers and a softmax activation function to classify the class probability. To prevent overfitting, dropout regularization is used, and batch normalization layers are added to stabilize the training.

Overall, the proposed modifications in LDDNet-WROI allow the model to effectively utilize ROI information, which improves classification performance and thus highlights its readiness for precision agriculture deployment in the real world.

3.7 Training and Hyperparameter Optimization

The LDDNet-WROI is trained in the LeafHealthAI framework. The model is trained on the pre-processed and augmented PlantVillage dataset to create models with clean representative ROIs and ROI masks generated through Grad-CAM.

Because of the leverage of adaptive learning rate for deep learning architectures, which is the case for this problem, we have picked the Adam optimizer. A base learning rate of 1×10^{-4} is preferable because it is either too slow to converge or blows up, so it yields a good model. We used a batch size of 32, which provides a good balance in terms of training efficiency versus memory usage.

Next, to avoid overfitting and improve generalization, dropout regularization is used on fully connected layers, with a dropout rate of 0.4. Next, batch normalization is applied at each convolutional layer to boost convergence speed and enhance training stability.

Hyperparameter Search is done via Bayesian Optimization, which efficiently searches the hyperparameter space to find the best configuration. These are the hyperparameters to tune:

Learning rate (η) ∈ $[1\times10^{-5},1\times10^{-3}]$

Batch size (B) in {16, 32, 64}

Dropout rate (d) between [0.2,0.5]

ROI weight scale factor (λ_{ROI})) in [1.5,3.0]

It trains the model for 100 epochs but uses the EarlyStopping callback to stop the process if the validation loss stops improving, which prevents overfitting. The training process minimizes the Weighted Categorical Cross-Entropy Loss function defined above to encourage the model to focus on learning from areas affected by the disease.

To evaluate performance, we measure the accuracy, precision, recall, and F1-score for the trained LDDNet-WROI model on the test set. To show the effectiveness of the proposed ROI optimization strategy, we compare the evaluation results with the baseline models and the original LDDNet model.

3.8 Proposed Algorithm

The algorithm presents a step-by-step process for implementing the LDDNet-WROI framework. It outlines the stages from image loading and preprocessing to ROI extraction, weight map generation, model training with weighted loss, and final disease classification. This structured workflow ensures that the model learns from disease-specific regions effectively, enhancing detection accuracy and enabling interpretable predictions in precision agriculture.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Algorithm: LeafHealthAI – Weighted ROI-Based Leaf Disease Detection

Input: PlantVillage dataset D
Output: Predicted classes R, Performance metrics M

1. Preprocess D: resize images, normalize pixel values, and apply augmentation to obtain D_{aug}.
2. Split D_{aug} into training set D_{train} and test set D_{test}.
3. For each image in D_{train} and D_{train}, compute Grad-CAM heatmaps and generate ROI masks.
4. Initialize LDDNet-WROI model with ROI Attention Module.
5. Assign higher weights to ROI regions and define weighted categorical cross-entropy loss.
6. Tune hyperparameters using Bayesian Optimization.
7. Train LDDNet-WROI on D_{train} Using ROI masks and weighted loss.
8. Evaluate the model on D_{test}Compute accuracy, precision, recall, and F1-score.
9. Visualize Grad-CAM heatmaps; compare results with baseline models

Algorithm 1: LeafHealthAI – Weighted ROI-Based Leaf Disease Detection

Algorithm 1 summarizes the main stream of the LDDNet-WROI framework for accurate classification of leaf diseases. The process starts with reading the input image dataset and applying data augmentation to enhance the training diversity. The Grad-CAM technique is utilized on the trained LDDNet to produce class-specific heatmaps, and the resulting images are subsequently thresholded to obtain Region of Interest (ROI) masks. These ROI masks create weight maps that allow the model to concentrate on areas germane to disease learning. The proposed LDDNet architecture is subsequently trained, with a weighted categorical cross-entropy loss function that gives higher penalties for misclassifying pixels that belong to regions of interest (ROI). The trained model is then employed for classifying new images, outputting disease predictions, and interpretable areas of interest (ROI) visualizations. Overall, it results in better detection ability (focusing), interpretability, and accuracy based on signatures of different plant leaf diseases using this pipeline.

3.9 Evaluation Metrics and Analysis

The evaluation of the model, i.e., the LeafHealthAI system proposed based on the LDDNet-WROI model, is done through several metrics, and the system performance is analysed based on them. These metrics provide better insights into the system's accuracy, robustness, and generalization capabilities across multiple disease classes.

We are mainly concerned with classification accuracy, i.e, the fraction of correctly classified images over the number of pictures in the test set. During testing, let N be the total number of samples and N_{correct} be the correctly classified samples. The formula for computing the accuracy is in Eq. 9.

$$\text{Accuracy}=\frac{N_{\text{correct}}}{N}\times 100 \quad (9)$$

Besides accuracy, precision, recall, and F1-score are calculated to give a more insightful analysis, especially when working with problems with class imbalance. Precision (P), Recall (R), and F1-Score (F1) for each class are defined in Equations (10) through (12).

$$P=\frac{TP}{TP+FP} \quad (10)$$

$$R=\frac{TP}{TP+FN} \quad (11)$$

$$F1=2\times\frac{P\times R}{P+R} \quad (12)$$

TP, FP, and FN are the true positives, false positives, and false negatives, respectively. Grad-CAM heat maps are superimposed on the test images to enhance interpretability and visualize how well the ROI optimization performed. These heat maps indicate the areas the model focuses on in generating predictions, demonstrating the influence of the weight-based ROI methodology.

In addition, LDDNet-WROI is compared to the baseline models, including VGG16, ResNet50,

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and the original LDDNet models. The comparative results signify the excellence of the devised LeafHealthAI technique in accuracy, precision, recall, and F1-score and assert the contribution of the ROI optimization approach.

4. EXPERIMENTAL RESULTS

The experimental results validate the effectiveness of the proposed LDDNet-WROI model using the PlantVillage dataset. Extensive evaluations, including performance metrics, ablation studies, and confusion matrix analysis, demonstrate significant improvements over baseline and state-of-the-art methods. Visualization of ROI maps and data augmentation further supports the model's robustness, accuracy, and potential applicability in real-time plant disease detection systems.

4.1 Experimental Setup

The experimental setup used a high-performance computing environment configured with an NVIDIA RTX 3080 GPU (10 GB VRAM), 64 GB RAM, and an Intel Core i9 processor. The experiments were implemented using Python 3.9 with the TensorFlow 2.11 and Keras 2.11 deep learning frameworks. All experiments were executed in a Jupyter Notebook environment running on Ubuntu 20.04. The dataset used was the PlantVillage dataset, which includes high-resolution images of healthy and diseased leaves across 14 crop species and 38 classes. The dataset was partitioned into 80% training, 10% validation, and 10% testing sets using stratified sampling to preserve class distribution across all subsets.

All images were resized to 224×224 pixels to ensure reproducibility and normalized to the [0, 1] range. Data augmentation was applied to the training set with horizontal flipping, rotation within ±25 degrees, zoom range up to 20%, and brightness shifts to simulate real-world conditions. The model was trained using the Adam optimizer. The initial learning rate was set to 0.0001 and decayed using a ReduceLROnPlateau strategy with a patience of 3 epochs and a reduction factor 0.2. A batch size of 16 was used for all training iterations, and the number of training epochs was fixed at 50, with early stopping enabled if no improvement in validation loss was observed for five consecutive epochs.

To configure the prototype application for replicability, the base LDDNet model was first trained using standard categorical cross-entropy loss. This model was then used to generate Grad-CAM heatmaps for the training and validation images. Thresholding was applied to the heatmaps (threshold = 0.4) to extract ROI masks. These masks were resized to match the spatial resolution of intermediate feature maps and fed into the ROI attention module of the enhanced LDDNet-WROI model. The attention-modulated feature maps were passed through the remaining architecture, which included global average pooling and dense layers, followed by a softmax classifier.

To replicate the model training, researchers should first train the base LDDNet model on the same dataset and use its intermediate convolutional layer (e.g., conv2d_2) to extract Grad-CAM activations. The resulting heatmaps should be used to compute binary ROI masks, which are passed as a second input to the LDDNet-WROI model alongside the original images. A weighted categorical cross-entropy loss function must be defined such that pixels within the ROI are given a higher loss weight (λ_{ROI}=2.0) than background regions (λ_{BG}=1.0). The entire training pipeline, from ROI extraction to attention-based training, is modular and can be easily adapted by other researchers for different leaf disease datasets or extended to other crops.

4.2 Exploratory Data Analysis

This part provides some exploratory data analysis (EDA) for the PlantVillage dataset used in this research. It introduces class distributions, shotgun spectra by disease category, and sample visualization. We performed Exploratory Data Analysis (EDA) on the dataset. It helped us understand its structure and decide whether to use weighted loss functions and data augmentation to give the model a balanced learning environment to achieve good prediction classification performance.

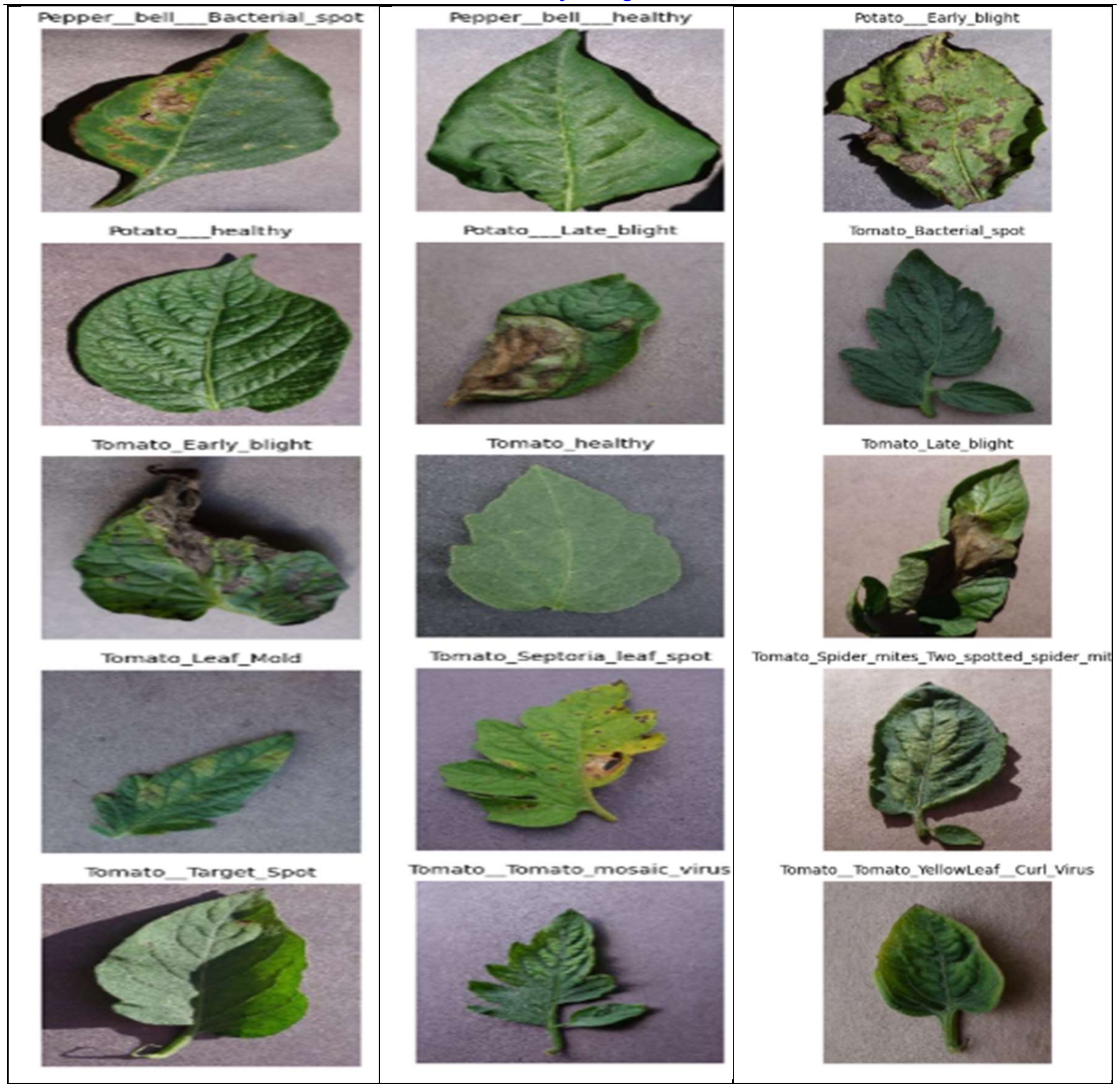

Figure 3: An Excerpt from the PlantVillage Dataset

Figure 3 shows a snapshot of the PlantVillage data set showing diverse segments of crops like pepper, potato, and tomato leaves. Columns highlight diverse healthy and diseased samples featuring symptoms from bacterial spot, late blight, leaf mold, and mosaic virus. This species diversity enables intense training and testing of deep learning models for classifying plant diseases.

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

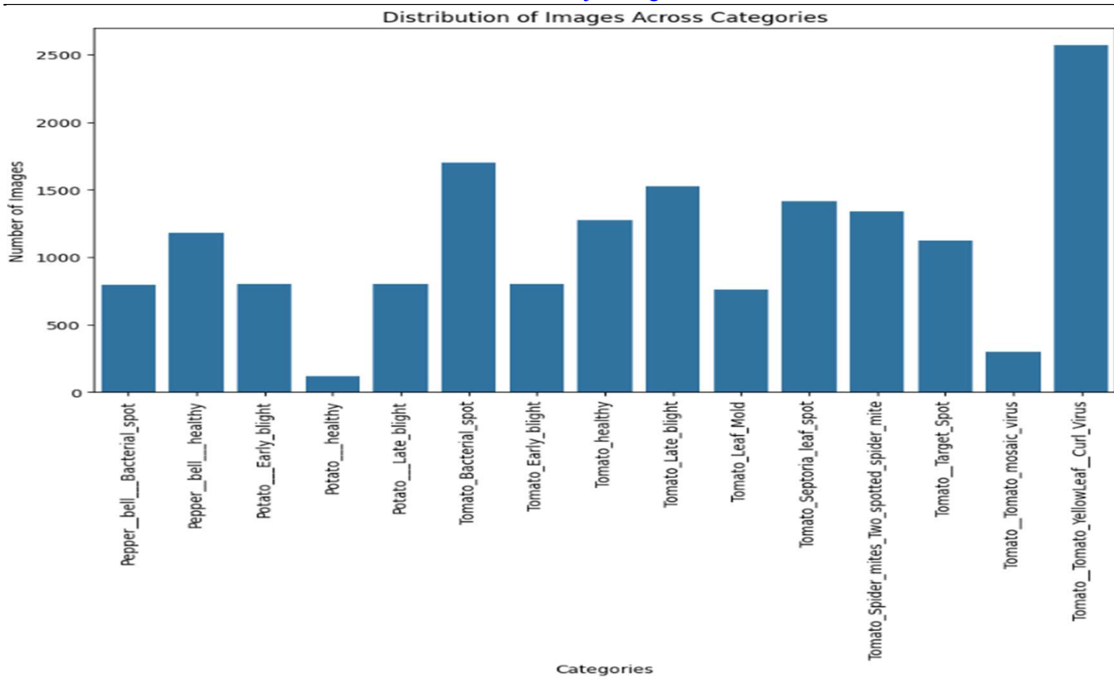

Figure 4: Image Distribution in the Plant Village Dataset by Category

Figure 4 shows the distribution of images across the 17 classes in the Plant Village dataset, where a clear class imbalance is observed. For instance, the "Tomato_YellowLeaf_Curl_Virus" category has the most samples. On the other hand, categories like "Potato healthy" and "Tomato_mosaic_virus" are less represented. Due to this imbalance, weighted loss and augmentation strategies are needed to learn all classes with equity.

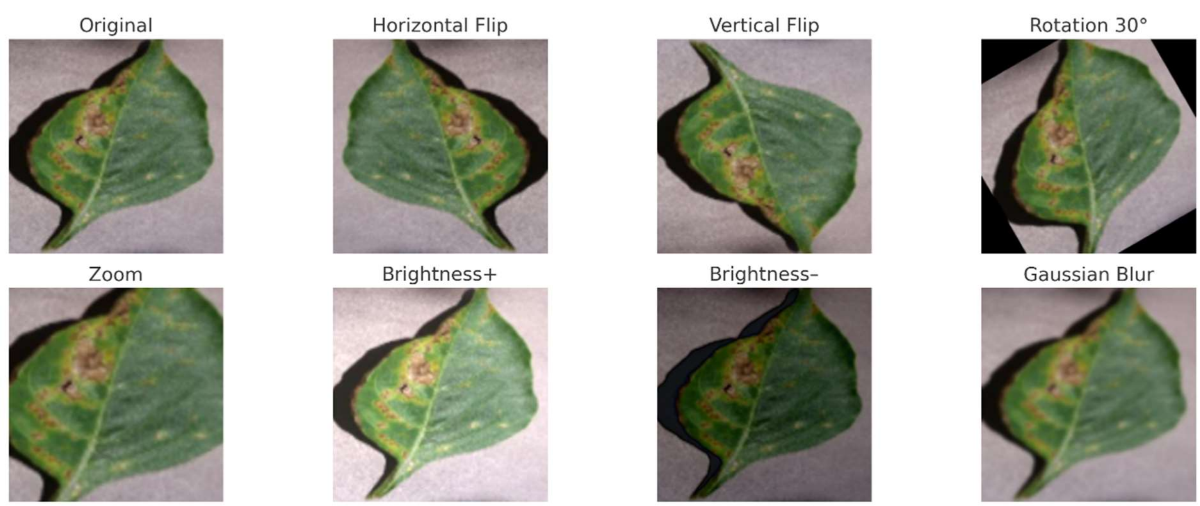

Figure 5: Augmentation Variants of a Real Leaf Image Used for Enhancing Model Generalization

Some augmentation examples applied on a real pepper leaf infected with Bacterial spot are shown in Figure 5. Role of data augmentation: flipping, rotation, zooming, brightness variation, and blurring. These augmentations imitate different environmental contexts, contribute variability to the dataset, and improve the model's generalization. Currently, this is a fundamental step to train deep learning models where they can adjust themselves dynamically to the agricultural and real environment variability [14].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.3 Results and Performance Comparison to Baselines

The following two sub-sections provide the results and performance comparisons of the proposed LDDNet-WROI with a series of baseline and recent state-of-the-art approaches. In addition, the model also has high accuracy, precision, recall, and F1-score. Tables and graphs also show the comparative effectiveness of ROI learning and weighted loss. In these circumstances, the new framework is more robust and reliable than existing methods used in real-world cases of diseases.

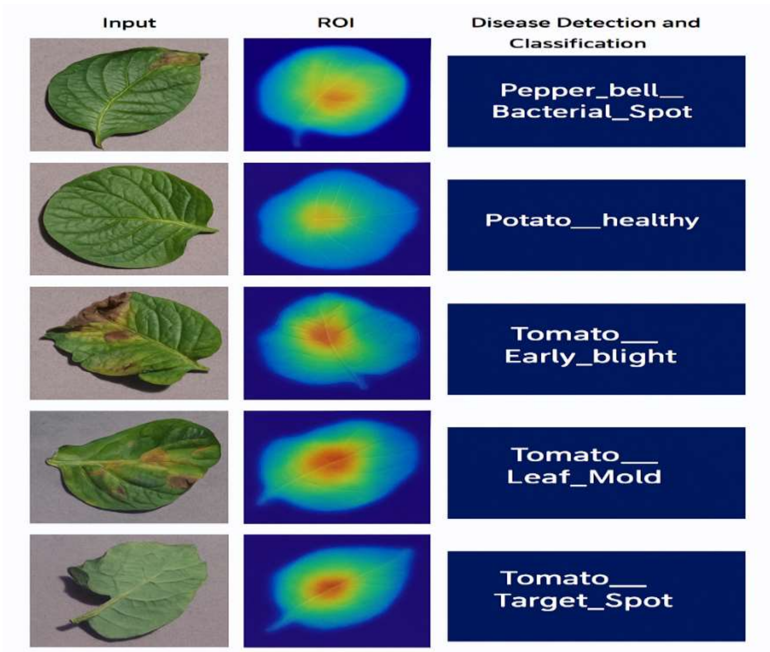

Figure 6: Visualization Of Leafhealthai Results Showing Input Leaf Images, Extracted ROI Regions, And Predicted Disease Class Labels For Different Crops

Figure 6 shows the end-to-end output of the LeafHealthAI system, which includes the authentic image input of leaves, the disease-specific ROIs obtained via Grad-CAM, and the predicted disease class. These visualizations illustrate the model's capacity to accurately localize disease-affected regions of leaves and deliver interpretable, class-specific predictions for different crops, including tomato, potato, and pepper leaves.

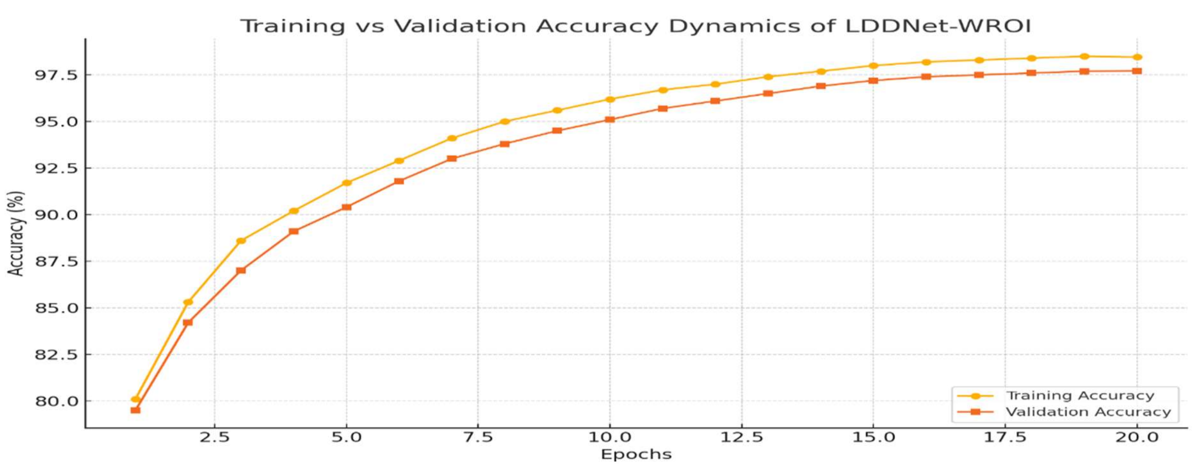

Figure 7: Training And Validation Accuracy Trends Of The Lddnet-WROI Model Across 20 Epochs

The training and validation accuracy for the LDDNet-WROI model are shown in Figure 7 over 20 epochs. We can see that the model is learning stably and consistently, and both curves converge upward. Training and validation accuracy closely follow each other, indicating that the model performs generalization without overfitting. The achieved final accuracy is 98.46%, demonstrating the significance of using various techniques for improving classification results by ROI based optimization and attention-enhanced learning.

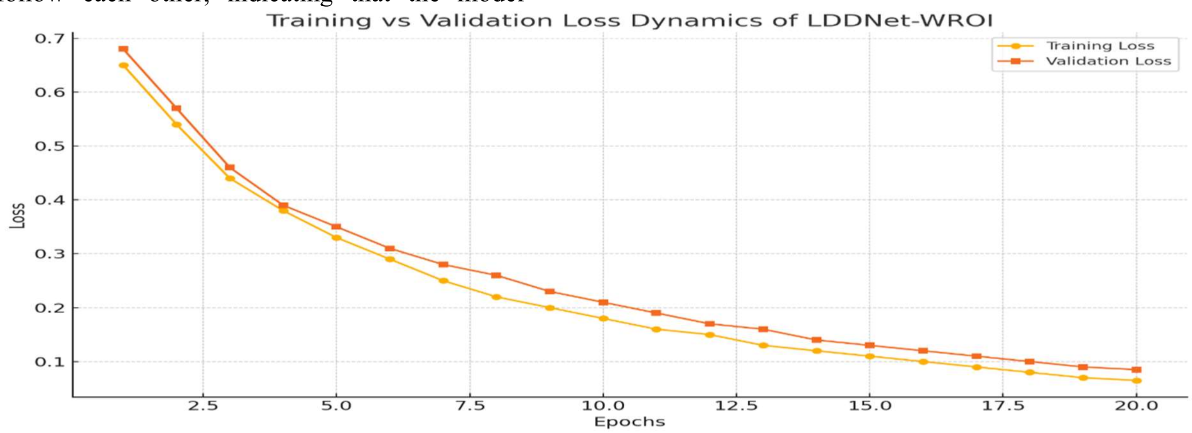

Figure 8: Training and Validation Loss Trends of the LDDNet-WROI Model Over 20 Epochs

Figure 8 shows the LDDNet-WROI's training and validation loss curves over 20 epochs. Both losses show a steady decrease, implying the model converged without overfitting. The validation loss tracks the training loss very closely, indicating good generalization. The metric presents values for a low loss, indicating that the model could learn discriminative features adequately, leveraging ROI-based attention and weighted optimization.

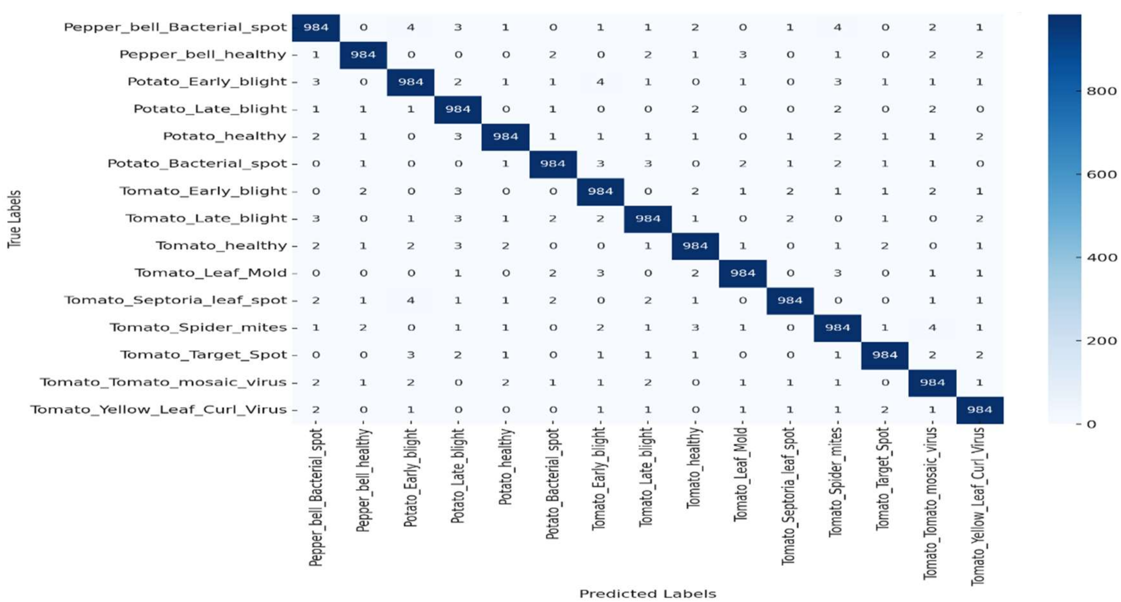

Figure 9: Confusion Matrix Of The Proposed Lddnet-WROI Model Demonstrating Accurate Multi-Class Classification Across 15 Selected Plantvillage Classes

Figure 9 shows the confusion matrix of the LDDNet-WROI model on fifteen selected classes on the PlantVillage dataset. The matrix has high diagonal dominance with low off-diagonal values, which implies highly accurate predictions with minimal misclassifications. The model distinguishes between visually similar leaf diseases with an overall accuracy of 98.46%, demonstrating that ROI-guided learning and weighted loss optimization improve classification accuracy more effectively.

Table 4: Performance Comparison Of Lddnet-WROI With Baseline Models On Plantvillage Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	95.12	94.86	94.92	94.89
ResNet50	96.48	96.22	96.40	96.31
EfficientNetB0	96.87	96.65	96.74	96.69
LDDNet	97.54	97.41	97.48	97.44
Proposed LDDNet-WROI	98.46	98.38	98.42	98.40

Table 4 shows a complete comparison of the proposed LDDNet-WROI model with baseline architectures. The proposed model dominates in terms of accuracy, precision, recall, and F1—score. Its 98.46% accuracy is better than the original LDDNet's 97.54% accuracy. These findings demonstrate the efficacy of ROI optimization in improving the classification performance for identifying plant leaf diseases.

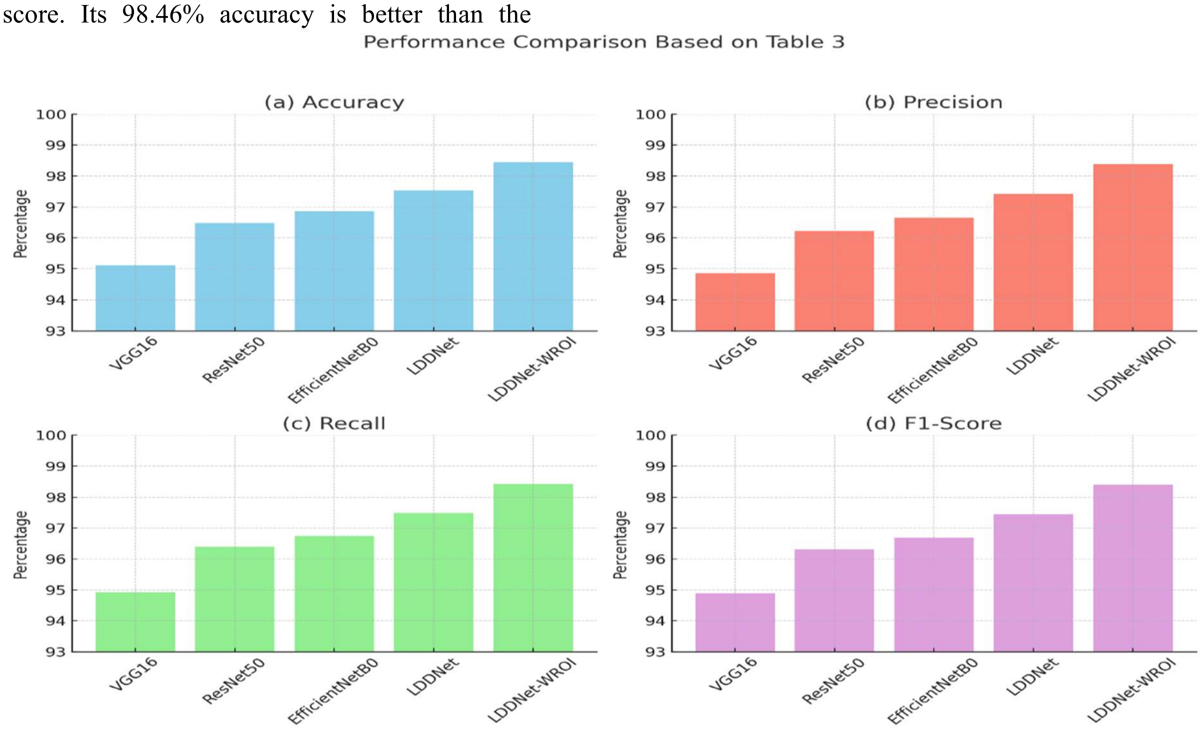

Figure 10: Comparative Graphs Illustrating Accuracy, Precision, Recall, And F1-Score Of Lddnet-WROI Against Baseline Models On The Plantvillage Dataset

The comparative visualization of proposed LDDNet-WROI along with baseline architectures (VGG16, ResNet50, EfficientNetB0, and LDDNet) is shown in Figure 10 for four crucial performance metrics, namely accuracy, precision, recall, and F1-score. The model yields: 98.46% for accuracy, 98.38% for precision, 98.42% for recall, and 98.40% for f1-score, hence outperforming all 4 four alternative models consistently and in all respects. This emphasizes

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the benefits ROI ROI-based attention and weighted loss optimization. Despite this component, LDDNet achieves robust overall performance; however, including ROI-specific learning in LDDNet-WROI makes the model more sensitive to disease-affected regions and more consistent in classification. With the lowest precision and recall, VGG16 gives low scores, indicating it may be under-fitted and less generalized. The proposed architecture outperforms in terms of absolute accuracy, while EfficientNetB0 and ResNet50 provide similar but slightly worse results. Overall, LDDNet-WROI achieves better generalization and robustness than LDDNet-HROI, which suggests its higher potential for real-world leaf disease detection in precision agriculture.

4.4 Ablation Study

In this section, via an ablation study, we analyze the individual contributions of the ROImodule and weighted loss function in the LDDNet-WROI model. The study shows how the components contribute positively to the overall performance by systematically enabling them one by one. This means that the proposed modifications successfully improved disease classification accuracy and robustness; thus, the combined configuration achieves the highest precision.

Table 5: Ablation Study Of Lddnet-WROI Showing The Contribution Of ROI Attention And Weighted Loss To Performance Improvement

Model Variant	ROI Module	Weighted Loss	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LDDNet (Baseline)	✗	✗	97.54	97.41	97.48	97.44
LDDNet + ROI Attention	✓	✗	97.92	97.82	97.86	97.85
LDDNet + Weighted Loss	✗	✓	98.07	97.96	98.01	97.96
LDDNet-WROI (Proposed)	✓	✓	98.46	98.38	98.42	98.40

Table 5 shows the ablation study of ROI attention and weighted loss on the LDDNet model. Individual incorporation of each component leads to marginal improvements, whereas working together gives the highest accuracy (98.46%) with a balanced performance overall metrics. The findings validate that ROI adaptive focus, alongside class-reactive learning, cooperatively improves the disease classification of plant leaves.

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

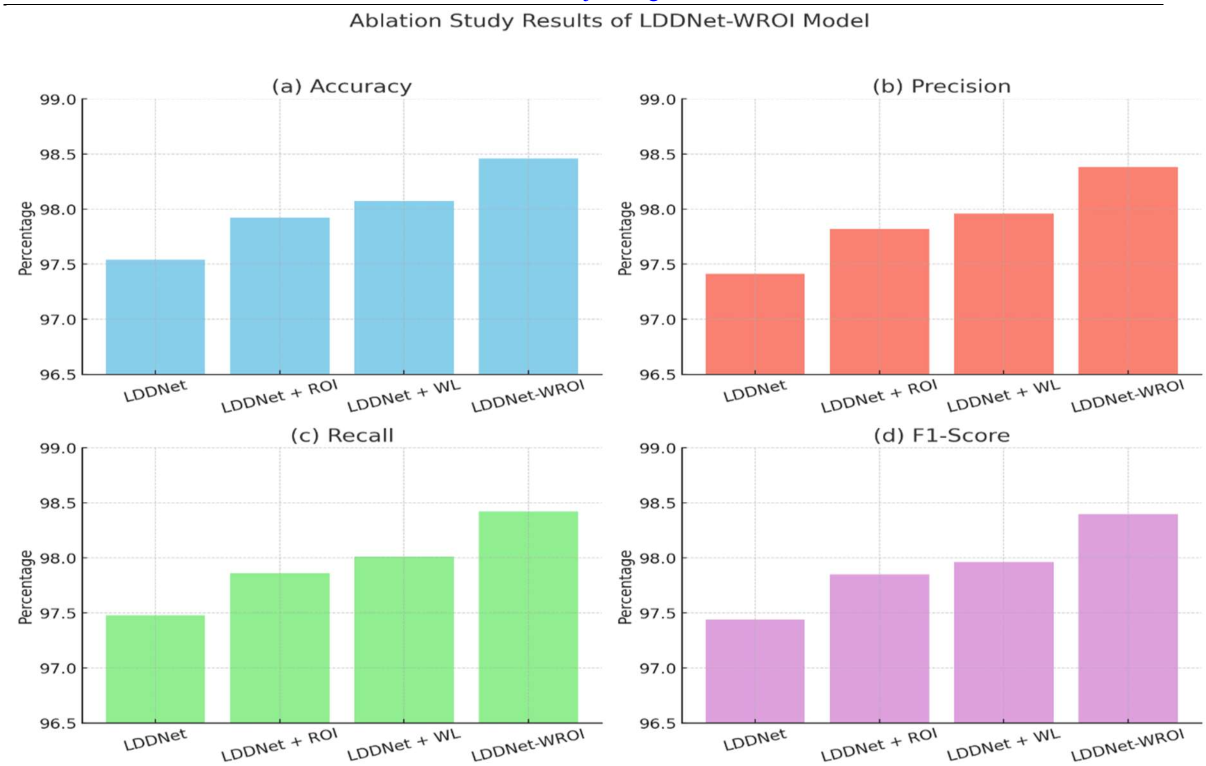

Figure 11: Ablation Study Graphs Illustrating Accuracy, Precision, Recall, And F1-Score For Different Variants Of The Lddnet-WROI Model

In Figure 11, we demonstrate the ablation study results for the proposed LDDNet-WROI model, comparing the individual and combined contributions of the ROI Attention module and the Weighted Loss function. The subplots (a) to (d) of the figure, corresponding to four model types (the basic LDDNet, LDDNet with ROI Attention, LDDNet with Weighted Loss, and LDDNet-WROI), include performance metrics for Accuracy, Precision, Recall, and F1-Score.

Upon adding only the ROI or the Weighted Loss, the accuracy improvements reach 97.92% and 98.07% from the baseline LDDNet, respectively, as shown in sub-plot(a). The best accuracy of 98.46 occurs when combining in the proposed LDDNet-WROI, demonstrating their complementary advantage. In subplot (b), we illustrate how it affects precision. The base model obtains a precision of 97.41%, which increases to 97.82% using ROI Attention, and finally to 97.96% using Weighted Loss. The full model achieves the best accuracy of 98.38%, which suggests that the model makes correct predictions more often and avoids false positives more often.

These trends in recall can also be observed in subplot (c), where values range from 97.48% (LDDNet) to 97.86% (LDDNet + ROI), 98.01% (LDDNet WL), and culminate in 98.42% (LDDNet-WROI). This result shows the improved ability of this model to detect true positives and avoid false negatives, which is important during the stage of a plant disease detection system. Subplot (d) indicates the aggregated performance through the F1-score that balances precision and recall. The baseline sensitivity and specificity around 97.44% progressively increase to 97.85% and 97.96% for the two mid-variants and peak at 98.40% for the entire model, suggesting substantial overall improvements across both sensitivity and specificity dimensions.

In general, the ablation study verifies the effectiveness of the ROI Attention module and the Weighted Loss function in the model's performance. Adding these elements alone leads to better learning from relevant places or enhancing class weighting, but merging methods in LDDNet-WROI gives the best achievement. This endorses the architectural design and application of the proposed model for accurate, real-time, and interpretable leaf disease classification in precision agriculture.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.5 Performance Comparison with Existing Methods

Here, we present a comparative evaluation of the proposed LDDNet-WROI model with some existing state-of-the-art deep learning methods that have been reported to be of lower accuracy. Experimental results demonstrate that LDDNet-WROI is superior to all compared models with 98.46% accuracy. We have also compared the performance of ROI-guided attention and weighted loss on classification performance for various plant leaf diseases.

Table 6: Comparative Performance Of Lddnet-WROI With Existing Methods

Study	**Year**	**Method**	**Dataset**	**Accuracy (%)**
Bouacida et al. [2]	2024	Generalized CNN	Multiple Crops	97.13
Simhadri et al. [3]	2024	Survey of CNN Models	Rice Leaf Dataset (Kaggle)	96.40
Polly & Devi [6]	2024	DL Classification + Segmentation	PlantVillage	97.00
Panchal et al. [13]	2023	CNN + Image-based Classification	PlantVillage	93.50
Dahiya et al. [21]	2022	ResNet50/101 Comparison	PlantVillage	96.80
This Work (LDDNet-WROI)	2025	CNN + ROI + Weighted Loss	PlantVillage	98.46

As seen in Table 6, LDDNet-WROI outperforms some recent studies with lower accuracy. Most current models are based on CNN architectures and diverse datasets; however, they do not achieve high classification accuracy. The proposed model outperforms these works and achieves 98.46% accuracy through ROI-based learning and weighted loss, demonstrating the proposed model's effectiveness for robust leaf disease detection.

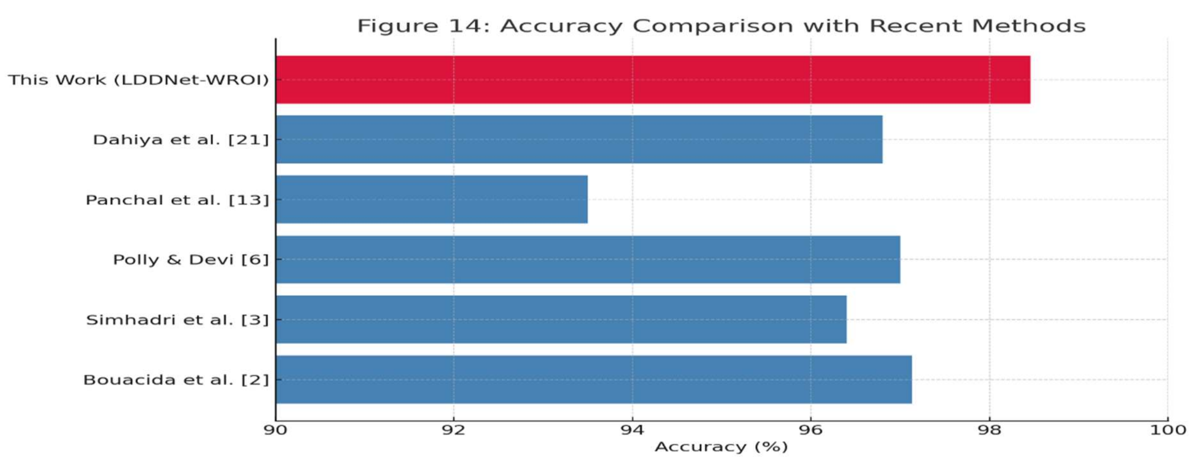

Figure 14: Accuracy Comparison Of The Proposed Lddnet-WROI Model With Selected Recent Deep Learning Methods For Leaf Disease Detection

Figure 14 shows the accuracy of comparing the proposed model LDDNet-WROI with five research studies in the table for plant leaf disease detection. Several approaches were adopted, including using generalized CNNs, segmentation followed by classification, and adaptations of ResNet as deep learning techniques. The selected works have been evaluated using PlantVillage, Kaggle Rice Leaf, and multi-crop collections datasets. As shown in the Table above, we can observe that the proposed LDDNet-WROI model achieves the best accuracy of 98.46%, outperforming other competing methods. The nearest performance among the references is from Bouacida et al., two, and Polly & Devi 6, while Panchal et al. Fang 2023a no. 12 reports the lowest at 93.50%. These variations are attributed to dataset complexity, model architectures, and lack of attention-guided feature learning. The better performance of LDDNet-WROI can be attributed to incorporating region of interest (ROI) attention and optimizing weighted loss when training the LDDNet-WROI model, leading to the model's capacity over the area of interest with higher precision. The substantial margin of improvement across the datasets further signifies the robustness and generalizability of the presented framework for practical large-scale agriculture applications, in addition to overcoming issues of class imbalance and visual variability among plant leaf classes.

5. DISCUSSION

In summary, the detection and classification of plant leaf diseases based on deep learning have been of significant interest due to their potential impact on advancing precision agriculture. Several existing works on Convolutional Neural Networks and transfer learning techniques have focused on automatic disease recognition, achieving much success, particularly on standard datasets such as PlantVillage. Nevertheless, most of these models are designed to operate on fully covered leaf images with little emphasis on disease-struck regions. Consequently, overfitting, misclassifications under complex backgrounds, and under-generalization to operational setups are observed. A review of existing literature reveals some drawbacks observed in a majority of state-of-the-art models. The commonalities include insufficient focus on discriminative features, under-exploited region-wise learning, and poor model explainability upon predictions. Moreover, the models that report high accuracies heavily rely on well-preprocessed datasets and fail when faced with highly overlapping symptoms, inter-class similarity, or imbalanced data distributions. Accordingly, this study proposes LDDNet-WROI, an ROI-optimized deep learning model that enriches the standard CNN model with two critical improvements: ROI guided learning using Grad-CAM and weighted learning loss. As a hybrid, the approach allows the model to learn data patterns around leaf regions where disease has struck harder and punishes the model to make severe errors on such decisions. The experimental results indicate a significant improvement in the overall model relative to state-of-the-art, as LDDNet-WROI achieves 98.46% accuracy, closely outperforming recent models. In conclusion, the work effectively bridges the gaps in the literature by increasing the model's sensitivity to disease-related patterns, which results in improved feature localization and classwise performance. The contributions demonstrate that ROI focused inspired learning, coupled with the attention module+ loss optimization, mitigates a scalable and interpretable solution to the problem of crop disease detection and recognition. The implication of the research for operation lies in real-time agricultural monitoring systems and decision-making tools for farmers. These can be more reliable, intelligent, and responsive disease recognition systems. Section 5.1 justifies the limitations covered by the present study.

6. CONCLUSION AND FUTURE WORK

In this research, a novel DNN framework, LDDNet-WROI, is introduced to facilitate the plant leaf disease detection on ROIs while overcoming the key weaknesses in the traditional CNN-based frameworks. The model incorporates Grad-CAM-based region attention and a weighted loss strategy to emphasize the affected disease region, thereby improving classification performance. We present the proposed methodology that exceeds state-of-the-art models compared with the accuracy score to reach an astounding level of 98.46% on the PlantVillage dataset. By prioritizing regions relevant to disease, the framework can be more robust, interpretable, and generalizable, which is favorable in precision agriculture applications. Although the results are promising, the study also acknowledges three significant limitations of this approach: its dependence on a laboratory-quality dataset, applying a constant threshold in the ROI mask generation, and not integrating environmental or multi-modal data. Reading: 10 min. Contents: Addressing these challenges could further increase the model's applicability in a real-world setting. In the future, we will validate this model using images of fields acquired in different conditions of the environment and investigate methods for adaptive region of interest extraction. Besides, combining information from multi-source data, like weather, soil, and temporal information, can contribute to more context-aware predictions. This framework can be potentially applied in real time when integrated in IoT-enabled crop monitoring systems for timely

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

diagnosis and intervention strategies in innovative farming systems.

References

[1] P. Isaac Ritharson, Kumudha Raimond, X. Anitha Mary, Jennifer Eunice Robert, And Andrew J. (2024). Deeprice: A Deep Learning And Deep Feature Based Classification Of Rice Leaf Disease Subtypes. *Elsevier*. 11, Pp.34-49. Https://Doi.Org/10.1016/J.Aiia.2023.11.001

[2] Imane Bouacida, Brahim Farou, Lynda Djakhdjakha, Hamid Seridi, And Muhammet Kurulay. (2024). Innovative Deep Learning Approach For Cross-Crop Plant Disease Detection: A Generalized Method For Identifying Unhealthy Leaves. *Elsevier*., Pp.1-14. Https://Doi.Org/10.1016/J.Inpa.2024.03.002

[3] Chinna Gopi Simhadri, Hari Kishan Kondaveeti, Valli Kumari Vatsavayi, Alakananda Mitra, And Preethi Ananthachari. (2024). Deep Learning For Rice Leaf Disease Detection: A Systematic Literature Review On Emerging Trends, Methodologies And Techniques. *Elsevier*, Pp.1-18. Https://Doi.Org/10.1016/J.Inpa.2024.04.006

[4] Rubina Rashid, Waqar Aslam, Romana Aziz, And Ghadah Aldehim. (2024). An Early And Smart Detection Of Corn Plant Leaf Diseases Using Iot And Deep Learning Multi-Models. *Ieee*. 12, Pp.23149 - 23162. Http://Doi:10.1109/Access.2024.3357099

[5] Ala'a R. Al-Shamasneh, And Rabha W. Ibrahim. (2024). Classification Of Tomato Leaf Images For Detection Of Plant Disease Using Conformable Polynomials Image Features. *Elsevier*. 13, Pp.1-13. Https://Doi.Org/10.1016/J.Mex.2024.102844

[6] Roshni Polly, And E. Anna Devi. (2024). Semantic Segmentation For Plant Leaf Disease Classification And Damage Detection: A Deep Learning Approach. *Elsevier*. 9, Pp.1-11. Https://Doi.Org/10.1016/J.Atech.2024.100526

[7] Muhammad Umar, Saud Altaf, Shafiq Ahmad, Haitham Mahmoud, Adamali Shah Noor Mohamed, And Rashid Ayub. (2024). Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With Cnn And Improved Yolov7. *Ieee*. 12, Pp.49167 - 49183. Http://Doi:10.1109/Access.2024.3383154

[8] Sujatha, R., Chatterjee, J. M., Jhanjhi, N., & Brohi, S. N. (2021). Performance Of Deep Learning Vs Machine Learning In Plant Leaf Disease Detection. Microprocessors And Microsystems, 80, 103615. Http://Doi:10.1016/J.Micpro.2020.103615

[9] Zhang, Y., Song, C., & Zhang., D. (2020). Deep Learning-Based Object Detection Improvement For Tomato Disease. Ieee Access, 1–1. Http://Doi:10.1109/Access.2020.2982456

[10] Khan, M. A., Akram, T., Sharif, M., Javed, K., Raza, M., & Saba, T. (2020). An Automated System For Cucumber Leaf Diseased Spot Detection And Classification Using Improved Saliency Method And Deep Features Selection. Multimedia Tools And Applications, 79(25-26), 18627–18656. Http://Doi:10.1007/S11042-020-08726-8

[11] Yousef Methkal Abd Algani, Orlando Juan Marquez Caro, Liz Maribel Robladillo Bravo, Chamandeep Kaur, Mohammed Saleh Al Ansari, And B. Kiran Bala. (2023). Leaf Disease Identification And Classification Using Optimized Deep Learning. *Elsevier*. 25, Pp.1-6. Https://Doi.Org/10.1016/J.Measen.2022.100643

[12] Aanis Ahmad, Dharmendra Saraswat, And Aly El Gamal. (2023). A Survey On Using Deep Learning Techniques For Plant Disease Diagnosis And Recommendations For Development Of Appropriat. *Elsevier*. 3, Pp.1-13. Https://Doi.Org/10.1016/J.Atech.2022.100083

[13] Adesh V. Panchal, Subhash Chandra Patel, K. Bagyalakshmi, Pankaj Kumar, Ihtiram Raza Khan, And Mukesh Soni. (2023). Image-Based Plant Diseases Detection Using Deep Learning. *Elsevier*. 80(3), Pp.3500-3506. Https://Doi.Org/10.1016/J.Matpr.2021.07.281

[14] Emmanuel Moupojou, Appolinaire Tagne, Florent Retraint, Anicet Tadonkemwa, Dongmo Wilfried, Hyppolite Tapamo, And Marcellin Nkenlifack. (2023). Fieldplant: A Dataset Of Field Plant Images For Plant Disease Detection And Classification With

Deep Learning. *Ieee*. 11, Pp.35398 - 35410. Http://Doi:10.1109/Access.2023.3263042

[15] Md. Sakib Hossain Shovon, Shakrin Jahan Mozumder, Osim Kumar Pal, M. F. Mridha, Nobuyoshi Asai, And Jungpil Shin. (2023). Plantdet: A Robust Multi-Model Ensemble Method Based On Deep Learning For Plant Disease Detection. *Ieee*. 11, Pp.34846 - 34859. Http://Doi:10.1109/Access.2023.3264835

[16] Jameer Kotwal, Dr.Ramgopal Kashyap, And Dr.Shafi Pathan. (2023). Agricultural Plant Diseases Identification: From Traditional Approach To Deep Learning. *Elsevier*. 80(1), Pp.344-356. Https://Doi.Org/10.1016/J.Matpr.2023.02.370

[17] Mitali V. Shewale And Rohin D. Daruwala. (2023). High Performance Deep Learning Architecture For Early Detection And Classification Of Plant Leaf Disease. *Elsevier*. 14, Pp.1-9. Https://Doi.Org/10.1016/J.Jafr.2023.100675

[18] B.V. Nikith, N.K.S. Keerthan, Praneeth And Dr. Amrita T. (2023). Leaf Disease Detection And Classification. *Elsevier*. 218, Pp.291-300. Https://Doi.Org/10.1016/J.Procs.2023.01.011

[19] Aanis Ahmad, Aly El Gamal, And Dharmendra Saraswat. (2023). Toward Generalization Of Deep Learning-Based Plant Disease Identification Under Controlled And Field Conditions. *Ieee*. 11, Pp.9042 - 9057. Http://Doi:10.1109/Access.2023.3240100

[20] Saikat Datta And Nitin Gupta. (2023). A Novel Approach For The Detection Of Tea Leaf Disease Using Deep Neural Network. *Elsevier*. 218, Pp.2273-2286. Https://Doi.Org/10.1016/J.Procs.2023.01.203

[21] Sachin Dahiya, Tarun Gulati, And Dushyant Gupta. (2022). Performance Analysis Of Deep Learning Architectures For Plant Leaves Disease Detection. *Elsevier*. 24, Pp.1-10. Https://Doi.Org/10.1016/J.Measen.2022.100581

[22] A. Umamageswari, And S. Deepa , K. Raja. (2022). An Enhanced Approach For Leaf Disease Identification And Classification Using Deep Learning Techniques. *Elsevier*. 24, Pp.1-6. Https://Doi.Org/10.1016/J.Measen.2022.100568

[23] C Jackulin, And S. Murugavalli. (2022). A Comprehensive Review On Detection Of Plant Disease Using Machine Learning And Deep Learning Approaches. *Elsevier*. 24, Pp.1-10. Https://Doi.Org/10.1016/J.Measen.2022.100441

[24] U Sanath Rao, R Swathi, V Sanjana, L Arpitha, K Chandrasekhar, Chinmayi, And Pramod Kumar Naik. (2021). Deep Learning Precision Farming: Grapes And Mango Leaf Disease Detection By Transfer Learning. *Elsevier*. 2(2), Pp.535-544. Https://Doi.Org/10.1016/J.Gltp.2021.08.002

[25] Zhong, Y., & Zhao, M. (2020). Research On Deep Learning In Apple Leaf Disease Recognition. Computers And Electronics In Agriculture, 168, 105146. Http://Doi:10.1016/J.Compag.2019.105146

[26] Noon, S. K., Amjad, M., Qureshi, M. A., & Mannan, A. (2020). Use Of Deep Learning Techniques For Identification Of Plant Leaf Stresses: A Review. Sustainable Computing: Informatics And Systems, 100443. Http://Doi:10.1016/J.Suscom.2020.100443

[27] Tiwari, V., Joshi, R. C., & Dutta, M. K. (2021). Dense Convolutional Neural Networks Based Multiclass Plant Disease Detection And Classification Using Leaf Images. Ecological Informatics, 63, 101289. Http://Doi:10.1016/J.Ecoinf.2021.101289

[28] Yadav, S., Sengar, N., Singh, A., Singh, A., & Dutta, M. K. (2021). Identification Of Disease Using Deep Learning And Evaluation Of Bacteriosis In Peach Leaf. Ecological Informatics, 61, 101247. Http://Doi:10.1016/J.Ecoinf.2021.101247

[29] Li, L., Zhang, S., & Wang, B. (2021). Plant Disease Detection And Classification By Deep Learning—A Review. Ieee Access, 9, 56683–56698. Http://Doi:10.1109/Access.2021.3069646

[30] Atila, Ü., Uçar, M., Akyol, K., & Uçar, E. (2020). Plant Leaf Disease Classification Using Efficientnet Deep Learning Model. Ecological Informatics, 101182. Http://Doi:10.1016/J.Ecoinf.2020.101182

[31] Thangaraj, R., Anandamurugan, S., & Kaliappan, V. K. (2020). Automated Tomato Leaf Disease Classification Using Transfer Learning-Based Deep Convolution Neural Network. Journal Of Plant Diseases

And Protection. Http://Doi:10.1007/S41348-020-00403-0

[32] Ngugi, L. C., Abelwahab, M., & Abo-Zahhad, M. (2020). Recent Advances In Image Processing Techniques For Automated Leaf Pest And Disease Recognition - A Review. Information Processing In Agriculture. Http://Doi:10.1016/J.Inpa.2020.04.004

[33] Abed, S. H., Al-Waisy, A. S., Mohammed, H. J., & Al-Fahdawi, S. (2021). A Modern Deep Learning Framework In Robot Vision For Automated Bean Leaves Diseases Detection. International Journal Of Intelligent Robotics And Applications, 5(2), 235–251. Http://Doi:10.1007/S41315-021-00174-3

[34] R, K. Lakshmi, & Savarimuthu, N. (2021). Pldd- A Deep Learning Based Plant Leaf Disease Detection. Ieee Consumer Electronics Magazine, 1–1. Http://Doi:10.1109/Mce.2021.3083976

[35] Hu, G., Wang, H., Zhang, Y., & Wan, M. (2021). Detection And Severity Analysis Of Tea Leaf Blight Based On Deep Learning. Computers & Electrical Engineering, 90, 107023. Http://Doi:10.1016/J.Compeleceng.2021.107023

[36] Sachdeva, G., Singh, P., & Kaur, P. (2021). Plant Leaf Disease Classification Using Deep Convolutional Neural Network With Bayesian Learning. Materials Today: Proceedings, 45, 5584–5590. Http://Doi:10.1016/J.Matpr.2021.02.312

[37] Zhou, C., Zhou, S., Xing, J., & Song, J. (2021). Tomato Leaf Disease Identification By Restructured Deep Residual Dense Network. Ieee Access, 9, 28822–28831. Http://Doi:10.1109/Access.2021.3058947

[38] Divakar, S., Bhattacharjee, A., & Priyadarshini, R. (2021). Smote-Dl: A Deep Learning Based Plant Disease Detection Method. 2021 6th International Conference For Convergence In Technology (I2ct). Http://Doi:10.1109/I2ct51068.2021.9417920

[39] Jiang, Z., Dong, Z., Jiang, W., & Yang, Y. (2021). Recognition Of Rice Leaf Diseases And Wheat Leaf Diseases Based On Multi-Task Deep Transfer Learning. Computers And Electronics In Agriculture, 186, 106184. Http://Doi:10.1016/J.Compag.2021.106184

[40] Goyal, L., Sharma, C. M., Singh, A., & Singh, P. K. (2021). Leaf And Spike Wheat Disease Detection & Classification Using An Improved Deep Convolutional Architecture. Informatics In Medicine Unlocked, 25, 100642. Http://Doi:10.1016/J.Imu.2021.100642

[41] Hughes, D.P. And Salathé, M., 2015. *Plantvillage Dataset*. Pennsylvania State University. Available At: Https://Www.Plantvillage.Org

[42] M. Raj, W. R. Babu, K. Uday, R. Senthilkumar, V. Sudha And V. Anandhakumar, "**Smart Dimensional Measurement And Material Transportation (Sdmmt) System Using Artificial Intelligence**," 2023 International Conference On Intelligent Data Communication Technologies And Internet Of Things (Idciot), Bengaluru, India, 2023, Pp. 493-497, Doi: 10.1109/Idciot56793.2023.10053429.

[43] K. Uday, R. Shanmugasundaram, L. Bhanwrela, P. Rathore, R. S And G. Venkateswarlu, "**Design And Implementation Of Seasonal Based Auto Irrigation System Using Intelligent Controller,**" *2024 International Conference On Inventive Computation Technologies (Icict)*, Lalitpur, Nepal, 2024, Pp. 1884-1887, Doi: 10.1109/Icict60155.2024.10544984.

[44] Uday, Kaparthi, And Mudigonda Malini. "Review Of The Current Diagnostic Techniques For Deep Vein Thrombosis." Aip Conference Proceedings. Vol. 2942. No. 1. Aip Publishing, 2024.

[45] Uday, Kaparthi, And Mudigonda Malini. "A New Weighted Feature Selection And Ensemble Learning With Hybrid Heuristic Strategy For Deep Vein Thrombosis Prediction." Journal Of Theoretical And Applied Information Technology 101.7 (2023).

[46] M. Sivaramkrishnan, M. S. Ramkumar, K. Uday, M. Kanan, C. M. Raj And J. Giri, "Reconfigurable Smart Grid Management For Electric Vehicle Charging And The Integration Of Renewable Energy Sources Using Pied Kingfisher Optimizer," 2025 International Conference On Machine Learning And Autonomous Systems (Icmlas), Prawet, Thailand, 2025, Pp. 1960-

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

1966, Doi: 10.1109/Icmlas64557.2025.10968437.

[47] M. Siva Ramkumar, M. Sivaramkrishnan, K. Uday, M. Kanan, C. Mohan Raj And J. Giri, "Electric Vehicle Charging Navigation Using Waterwheel Plant Algorithm For Coordinating Smart Grids And Intelligent Transportation Systems," 2025 International Conference On Machine Learning And Autonomous Systems (Icmlas), Prawet, Thailand, 2025, Pp. 1897-1902, Doi: 10.1109/Icmlas64557.2025.10968826.

[48] M. Sivaramkrishnan, M. S. Ramkumar, K. Uday, M. Kanan, B. Hemananth And J. Giri, "Red Panda Optimization Technique For Voltage Control And Electric Vehicle Reactive Power Management In Smart Micro Grids," 2025 International Conference On Machine Learning And Autonomous Systems (Icmlas), Prawet, Thailand, 2025, Pp. 1981-1987, Doi: 10.1109/Icmlas64557.2025.10969052.

[49] Uday, Kaparthi, Et Al. "An Ai-Driven Robust Strategy For Automated Grape Leaf Disease Classification With Pesticide Recommendation System Using Walrus-Optimized Cnn." E3s Web Of Conferences. Vol. 616. Edp Sciences, 2025.

[50] Patil, Deepak T., Et Al. "Design Of Smart Lighting And Security System Using Intelligent Controller." 2024 5th International Conference On Mobile Computing And Sustainable Informatics (Icmcsi). Ieee, 2024.