

Plant Detection and Give its Detail Using AI

Gunjal.S.V.¹, Kshirsagar Gayatri Gajanan², Varade Kalyani Bhausaheb³, Shinde Snehal Raju⁴, Navale Pranjal Vikas⁵

¹Professor, Dept. of Cloud computing and big data, P.Dr.V.V.P. Institute of Technology and Engineering, Loni,

Maharashtra, India

^{2,3,4,5}Final year Diploma Dept. of Cloud computing and big data, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India

Abstract - The field of artificial intelligence includes deep learning. The benefits of AI and feature extraction have made it a hot topic in both academia and business in recent years. Many applications in the fields of speech recognition, image processing, and natural language processing have made extensive use of it. Additionally, it has emerged as a center of excellence for research on agricultural plant protection, including pest range assessment, plant disease recognition, and more. Deep learning's usage in plant disease recognition has the potential to increase research efficiency, speed up technological transition, make plant disease feature extraction more objective, and prevent the drawbacks of artificially selecting disease spot features. This article summarizes the latest developments in the use of deep learning for the purpose of identifying diseases in crop leaves. Using the deep learning and advanced imaging techniques of CenterNET ResNET, we highlight the current trends and problems in plant leaf disease identification in this research. We anticipate that this work will serve as an invaluable tool for scientists whose focus is on finding pest insects and illnesses in plants. At the same time, we also discussed some of the current challenges and problems that need to be resolved.

Key Words: Deep learning, plant leaf disease detection, visualization, small sample, hyperspectral imaging, Center NET Res NET.

1.INTRODUCTION

Agricultural output is negatively affected by the prevalence of plant diseases. More people will go hungry if we don't find ways to prevent plant diseases soon. The administration and decision-making of agricultural output rely heavily on early detection systems, which are essential for the effective prevention and control of plant

diseases. The identification of plant diseases has emerged as an important concern in the last several years. Leaves, stems, flowers, and fruits are the most common sites for disease symptoms on plants. In most cases, a distinct pattern can be observed in the presence of a disease or pest to aid in the diagnosis of anomalies. The leaves of a plant are often the first to show signs of disease, and they are also the most reliable source for identifying plant diseases. Typically, on-site identification of fruit tree diseases and pests is done by agricultural and forestry experts, or by farmers relying on their own knowledge. Not only is this approach subjective, but it is also tedious, difficult, and wasteful. In the identification procedure, less experienced farmers may make mistakes in judgment and utilize medications without thinking. In addition to causing needless economic losses, quality and output will pollute the environment. Research into the application of image processing techniques for plant disease recognition has recently gained a lot of attention as a potential solution to these problems.

Using the K-means clustering method to segment the lesions regions, combined the global color histogram (GCH) color coherence vector (CCV) local binary pattern (LBP), and completed local binary pattern (CLBP) to extract the color and texture features of apple spots, followed by three kinds of apple diseases detected and identified using improved support vector machine (SVM), and the classification accuracy reached 93%. This is an example of the general process of using traditional image recognition processing technology to identify plant diseases. Using stepwise discriminant and Bayesian discriminant principal component analysis (PCA), respectively, we studied four tomato leaf diseases: early blight, late blight, leaf mildew, and leaf spot. From the images of tomato leaf spots, we extracted 18 characteristic parameters, including color, texture, and shape information. The discriminant model was built and the

distinctive parameters were extracted using principal component analysis and Fisher discriminant methods. With one approach, the accuracy was 94.71% and with the other, 98.32%. Researchers focused on five different apple leaf diseases: speckled deciduous, yellow leaf, round spot, mosaic, and rust. Through the extraction of eight characteristics from the apple leaf spot image, including shape, texture, and color. The disorders were categorized and identified using the BP neural network model, which achieved an average recognition accuracy of 92.6%. Classified and recognized three rice diseases (blast, stripe blight, and bacterial leaf blight) using 63 parameters, including morphology, color, and texture features of disease spots on rice leaves. The highest recognition accuracy achieved was 97.2% using step-based discriminant analysis and the Bayesian discriminant method. While research on plant disease recognition using conventional image processing methods has yielded promising results—namely, a high rate of accurate disease recognition—the following caveats and limitations remain: 1) It takes a lot of time, effort, and subjectivity to complete the research links and procedures; 3) Spot segmentation is crucial; 4) testing the model's or algorithm's illness recognition ability in more complicated contexts is challenging; and 5) artificial feature extraction is highly relied upon.

[1] Muhammad Hammad Saleem et al. studied covers a range of unfilled research needs in deep learning-based plant disease detection. To that end, we provide a new dataset named NZDLPlantDisease-v1 and offer a DL-based method to identify and pinpoint the illness in five of New Zealand's most valuable horticultural export crops. When comparing the mean average precision with and without augmentation approaches, the region-based fully convolutional network (RFCN) emerged as the clear winner among the trained and tested DL architectures. The suggested approach is based on an exhaustive review of many methods that influence the unexplored deep learning model for plant disease detection tasks. In addition, after carefully examining position-sensitive score maps and anchor-box scales with aspect ratios, we suggest an improved version of the RFCN model.

[2] Vibhor Kumar Vishnoi et al. proposed to use photos of apple leaves to detect illnesses. Helping out novice apple orchardists and relieving pressure on plant pathologists are two potential benefits. For 1000 epochs, the model was trained on 31,171 apple leaves. On the Plant Village dataset, the model achieved an accuracy of 98%. Extensive testing shows that the suggested model outperforms a number of pre-trained CNN models.

Several metrics, such as accuracy and memory needs, showed that the method outperformed several other existing methods. The model's accuracy ranges from 97% to 99% across a variety of disorders. The model achieved a good balance between precision and accuracy. The suggested model is consistent and dependable, as shown by the AUC-ROC curve. Collecting additional high-quality leaf photos of apple plants grown in a variety of environments and at different phases of development could be an expansion of this effort. More rigorous trials might be conducted with the huge dataset that includes increased image variability, which would assist to improve the model's ability to detect diseases at different stages for different apple crop varieties.

[3] Emmanuel Moupojou et al. studied to aid researchers, we made available Field Plant, a collection of 5,170 photos of plant diseases that have been annotated and gathered from actual plantations. Plant pathologists have manually classified all of the photos in this collection, setting it apart from PlantDoc. It is possible to add new illness classes to the dataset, though. Since Field Plant is the first plant disease dataset to include annotated cassava photos, it could find extensive application in the study and management of plant diseases. The effectiveness of cutting-edge item detection and classification models was tested in a series of studies. Even while Field Plant outperformed PlantDoc in the classification assignment, the results demonstrate that current models are insufficient for reliable plant disease detection and classification using field-collected photos. For this reason, it is important to develop accurate models that can aid farmers in detecting crop illnesses and developing effective responses. Using model assembling in conjunction with image segmentation on field photos to separate leaves from a background image could be a great way to tackle this issue.

The second part of this report examines the prior research that was deemed a Literature Survey. Section 3, labelled "Proposed methodology," provides a comprehensive description of the proposed approach. The experimental evaluation is covered in Part 4, possible modifications are discussed in Section 5, and the essay concludes with a conclusion on the existing plan.

2. LITERATURE SURVEY

[4] Khalid M. Hosny et al. Accurated, an efficient convolutional neural network (CNN) model is created with few parameters. Additionally, a feature-fusion based approach is suggested for the classification of plant leaf diseases. Deep features can be combined with handmade

features derived by LBP using the suggested method. The training and testing of the suggested model were conducted using three publicly available PlantVillage datasets: Apple Leaf, Tomato Leaf, and Grape Leaf Databases.

[5] Chunduri Madhurya et al. Disease detection in plant leaves at an early stage is a difficult and intricate process. Slow detection speed, a large number of parameters, and poor efficiency in recognizing small dense patches are some of the constraints of deep-learning-based approaches to illness identification, despite the fact that these methods have demonstrated promising outcomes. In order to overcome these shortcomings, a new method for creating illness detection feature maps is suggested, which combines YR2S and PCFAN. In order to optimize classification, we use shufflenetv2 with ERSO. For segmentation, we use FCN-RFO to identify areas prone to diseases.

[6] Muhammad Hamza ASAD et al. studied centers on Kochia, a weed that outcompetes crops for nutrients due to its rapid proliferation and chemical resistance. Our study's overarching goal is to use satellite photography to identify patches of Kochia and high-resolution ground imagery to identify individual plants. The study's findings demonstrate that ResNet50-SegNet semantic segmentation is capable of detecting individual Kochia plants with an IOU of 0.78, mIOU of 0.8606, and fwIOU of 0.92. When Kochia grows in overlapping or obstructive ways across rows of crops, though, the model's accuracy can suffer. On the Kochia dataset, we examined multiple semantic segmentation topologies and discovered that SegNet achieved the best results in terms of IOUs. In order to identify Kochia patches based on densities in high-resolution ground pictures, we trained a model using satellite photography. This allowed us to utilize the model in fields where high-resolution ground imaging is not accessible.

[7] Natasha Nigar et al. proposed the devastating effects of plant diseases on agricultural productivity and farmers' ability to make a living are a major drag on our national economy. Fighting plant diseases is important for farmers' bottom lines and the economy as a whole. Here, the efficacy of an explainable artificial intelligence (XAI)-based deep learning-based plant disease detection system is detailed. By combining XAI approaches with powerful deep learning models, we can improve disease identification accuracy and make the results more interpretable. Using a dataset of 87,000 photos, this study develops the ML model using EfficientNetB0. On top of

that, the LIME framework is used to give insightful explanations that help in making smart decisions. In addition to demonstrating the model's efficient generalization, the visual explanations expose biases learned from photos of outliers.

[8] Mazin Abed Mohammed et al. introduce an approach called edge-cloud remote sensing data-based plant disease detection using deep neural networks with transfer learning, which tries to solve the problems like collecting data on a large scale, identifying diseases, and processing data efficiently and accurately across different platforms. We advocated for the integration of transfer learning with FCDCNN techniques that originate from combinatorial optimization issues. Data acquisition from dispersed plants was improved by optimizing training processing time and learning rate across numerous edge and cloud nodes using the convex function.

[9] Eman A. Al-Shahari et al. designed a novel APDDCM-SHODL strategy for environmentally responsible farming. To boost agricultural output within the framework of the Internet of Things (IoT), the suggested APDDCM-SHODL system seeks to detect the presence of plant diseases. The VMF methodology is the main tool used by the APDDCM-SHODL method to accomplish this. We also use the DenseNet-201 model to extract features. In addition, the DenseNet201 method's hyperparameters are fine-tuned using the SHO approach. In addition, the RSNN algorithm can be used to implement the classification approach. To find out whether the APDDCM-SHODL approach holds up in experiments, a quick series of simulations has been run. All things considered, the results show that the APDDCM-SHODL approach outperforms the competition. The system's usefulness rests in the fact that it provides accurate and timely data to farmers, who can then take preventative measures to limit the spread of diseases and improve their crop management.

[10] Rubina Rashid et al. developed an amalgamation of multi-contextual networks that automatically takes advantage of CNN techniques in many variants, forming a multi-model network. This is a high-level proposal that learns effective feature sets that are fused at the decision level by integrating RL-block and PL-blocks 1 and 2, with width cardinality and environmental parameters. For the suggested modeling accuracy to be effective, these feature sets are recognized at both the global and local levels. The suggested model is useful for choosing receptive fields' learning

parameters in order to examine feature maps at various layers.

[11] Diana Susan Joseph et al. proposed the food grains, including rice, wheat, and maize, were analysed in real-time using photographs sourced from various databases and the internet. Images of various disease severity levels were given importance because they help farmers and growers make the right judgments when the disease is still in its early stages. Less yield loss and financial damage can occur if diseases are detected early on. The current work involves the identification and classification of diseases affecting rice, maize, and wheat. The suggested MRW-CNN model, which is based on CNN-based deep learning models pre-trained on the ImageNet dataset using a deep transfer learning strategy, was fine-tuned using data downloaded from Keras. We trained all the models for 100 epochs.

[12] M. Pajany et al. presented the applying the OFDNN-PDDC method to remote sensing data collected by UAVs. The goal of the OFDNN-PDDC method is to accurately detect and categorize the various plant diseases. In order to improve the efficiency of plant disease diagnosis, the OFDNN-PDDC method employs a three-step procedure. First, the OFDNN-PDDC method learns intrinsic feature patterns from the remote sensed data using an upgraded ShuffleNetv2 model. In addition, the OFDNN-PDDC method uses the FRBM model for disease detection in plants. At last, the OFDNN-PDDC technique's hyperparameter is chosen using TCSSA..

[13] Anita Shrotriya et al. analysed shows that the CNN-RNN ensemble model works well and consistently when applied to cotton disease detection. An area under the curve (ROC) of 0.96 shows that the model performed very well and could reliably differentiate between healthy and sick cotton plants. Most of the probabilities cluster around 0 (diseased) and 1 (healthy), demonstrating discriminative solid power, meaning that the model is very confident in its predictions. Effective learning and good generalization to unseen data are suggested by the steady growth of both training and validation accuracy over the epochs, which converges around 0.85. As the epochs progress, the training and validation losses decrease, eventually reaching around 0.30, which means that the training process was successful and overfitting was modest.

[14] Ognjen Kundacina et al. introduced for use in thermal power plants as a CAD framework for PM, guaranteeing statistically valid control over the FPR

without the need for manual threshold setting. In order to achieve the study goal of creating a PM anomaly detection system that is statistically valid, the problem was framed as a hypothesis testing problem. For each test sample, marginal p-values were produced. We had to apply calibration-conditional p-value adjustments because the original FPR was higher than the chosen significance level, which is a result of the difficulty of doing multiple hypothesis tests with dependent tests. As shown by the high AUROC values (about 0.933), which indicate that the best-performing method had minimal effect on discriminative capacity, we assessed three different kinds of adjustments and found that the optimal one decreased FPR from 0.6541 to 0.0995. Improving maintenance efficiency and eliminating unnecessary interventions are both made possible by this strategy, which enables early fault identification with reduced false alarms.

[15] B. Ramana Reddy et al. proposed a convolutional neural network (CNN) and traditional image processing-based, lightweight system for the real-time diagnosis and severity assessment of plant diseases. With a training accuracy of more than 92%, the CNN was trained to categorize leaf pictures as either healthy or diseased. Moreover, the severity estimation module that was based on OpenCV offered quantitative insight into the infection extent that could be understood. A React Native mobile app with a Flask backend for computation incorporated both components. In just two seconds after uploading a picture of a leaf, users will get a diagnosis, a percentage of the severity, and a Grad-CAM heatmap. Because of this, the instrument is well-suited for use by farmers and other agricultural workers in the field in real time. Evaluation of the test set and qualitative assessments have confirmed the app's validity. Our solution provides a realistic compromise between performance, explainability, and readiness for deployment when compared to earlier methods.

3. METHODOLOGY

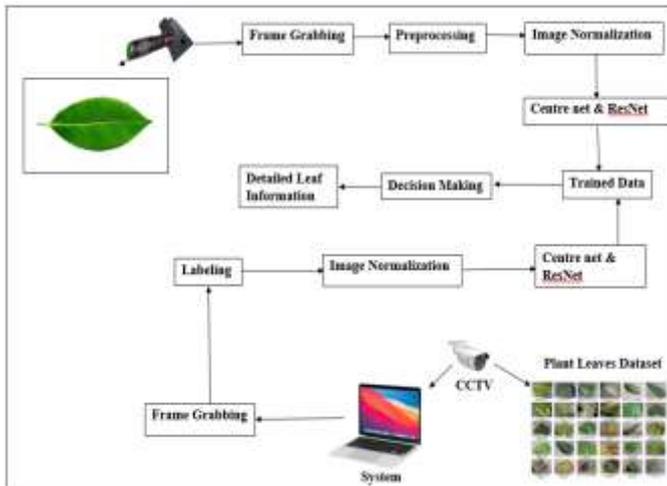


Fig 1: Overview Diagram

The steps of the overview diagram that are meant to detect plant leaves and provide detailed information about them can be described with the below mentioned steps.

Step 1: Dataset Generator

Using OpenCV, the first step of the process is to capture pictures of different plant leaves. During model testing, the Video Capture method in the CV2 package captures photos of plant leaves so that they can be detected and analyzed by the system. The leaf images are stored in the dataset folder. The plant leaf dataset contains images of different types of leaves collected from the plant leaves dataset. In preparation for the model's next stage, the gathered plant leaf photographs are saved in a folder.

Step 2: Data Labelling

This phase involves utilizing the labeling software to label the photos that were acquired in the previous stage. By importing the image into the labeling software, the user can indicate the coordinates of the leaf region. The coordinates such as x_1 , y_1 and x_2 , y_2 represent the rectangular area covering the leaf in the image. In order to train the model using ResNet and CentreNet, deep learning networks, the acquired coordinates are saved in an .xml file.

Step 3: System Setup

First things first, the required libraries and frameworks are installed in the working environment. These libraries help in performing image processing and deep learning operations. After setting up the environment, the system is ready to process the dataset and perform leaf detection tasks using the trained model.

Step 4: Prepare Training Data and Upload Image Set

To prepare the training data, the plant leaf images are uploaded to the system. The images are organized

properly so that the deep learning model can use them during training. The dataset folder contains all the images and annotation files related to plant leaves. These files are used for training and evaluating the model.

Step 5: Divide the image folders into train, validation, and test

After the dataset is uploaded, the next step is to organize the images into three different folders: train, validation, and test.

Train:

These images are used to train the deep learning model. During each training stage, the neural network processes images from the train dataset to learn the important features of plant leaves.

Validation:

Validation images are used to monitor the performance of the model during training and adjust parameters such as learning rate.

Test:

Test images are used to evaluate the final performance of the model after training is completed.

Step 6: Image Preprocessing and Normalization

In this stage, the plant leaf images undergo preprocessing before being given to the deep learning model. Preprocessing includes resizing images, removing noise, and adjusting image quality. After preprocessing, image normalization is applied to scale pixel values to a fixed range. This helps the model process images more efficiently and improves training performance.

Step 7: Set Up Training Configuration

Here, we configure the CentreNet and ResNet models for training. CentreNet is used for detecting the leaf region in the image, while ResNet is used for extracting features from the leaf image. The configuration includes training parameters such as learning rate, batch size, and number of training steps. These parameters control how the model learns from the dataset.

Step 8: Train Custom Model

In this step, the deep learning model is trained using the prepared dataset. The training process allows the model to learn patterns and features from the plant leaf images. During training, the model adjusts its internal weights to improve detection and classification accuracy.

Step 9: Testing the Model for Leaf Detection

In the final stage, the trained model is tested using new leaf images captured through the camera system. The system performs frame grabbing, followed by preprocessing and image normalization, and then the image is passed to the CentreNet and ResNet model. The

system detects the leaf and provides detailed leaf information as the final output.

4. RESULTS AND DISCUSSION

For the proposed model to detect Plant Leaf, a Windows-based PC with 16 GB of RAM and an Intel Core i7 CPU is required. For this experiment, the model draws on the Anaconda IDE's Spyder and Jupyter IDE sources. The parameters of the confusion matrix are used to conduct rigorous tests on the generated model. Equations for recall, precision, accuracy, and macro F1 specify the confusion matrix's parameters.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$\text{Precision}(P) = \frac{TP}{TP+FN} \tag{2}$$

$$\text{Recall}(R) = \frac{TP}{TP+FP} \tag{3}$$

$$\text{Macro-F1} = \frac{2 * P * R}{P + R} \tag{4}$$

Here, TP is True positive cases, TN is True Negative cases, FP is False positive cases and FN is False Negative cases.

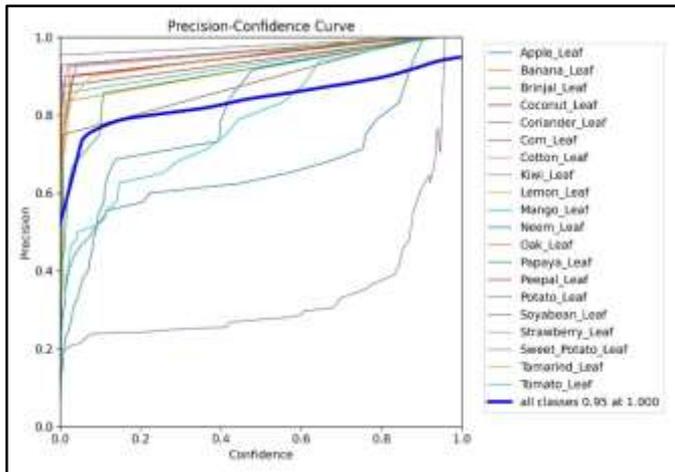


Fig 2: Precision–Confidence Curve

The figure illustrates the Precision–Confidence Curve used to evaluate the performance of the proposed leaf detection model. The graph represents the relationship between the precision value and confidence threshold for multiple plant leaf classes such as Apple Leaf, Banana Leaf, Mango Leaf, Neem Leaf, Potato Leaf, Tomato Leaf, and others. Each colored curve represents the detection performance for a specific leaf class. As the confidence threshold increases, the precision also improves, indicating more reliable predictions by the model. The thick blue line represents the overall performance of the model for all classes, achieving an average precision of approximately 0.95 at a confidence level of 1.0. This result shows that the model performs

effectively in detecting and classifying various plant leaves.

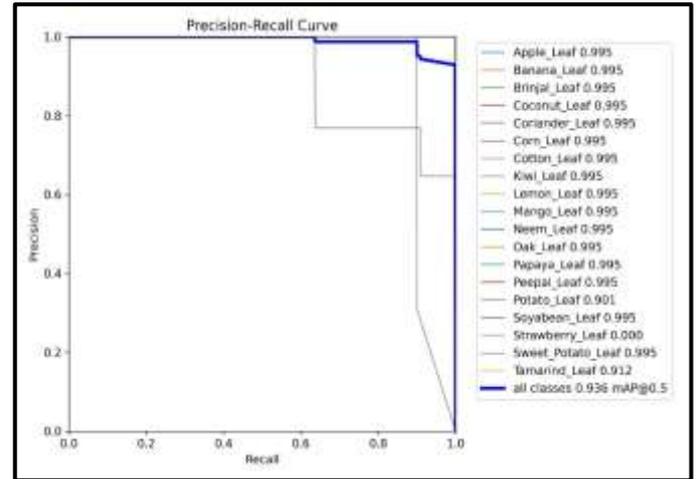


Fig 3: Precision-Recall Curve

The figure represents the Precision–Recall curve used to evaluate the performance of the proposed plant leaf detection model. The graph illustrates the relationship between precision and recalls values for different plant leaf classes such as Apple Leaf, Banana Leaf, Mango Leaf, Potato Leaf, Tomato Leaf, and others. Each curve corresponds to the detection performance of a specific leaf class. A higher precision value indicates fewer false positives, while a higher recall value indicates better detection of actual leaf instances. The curve demonstrates that the model maintains high precision and recall values across most classes, indicating strong detection performance. This result confirms that the proposed model is capable of accurately identifying and classifying different types of plant leaves.

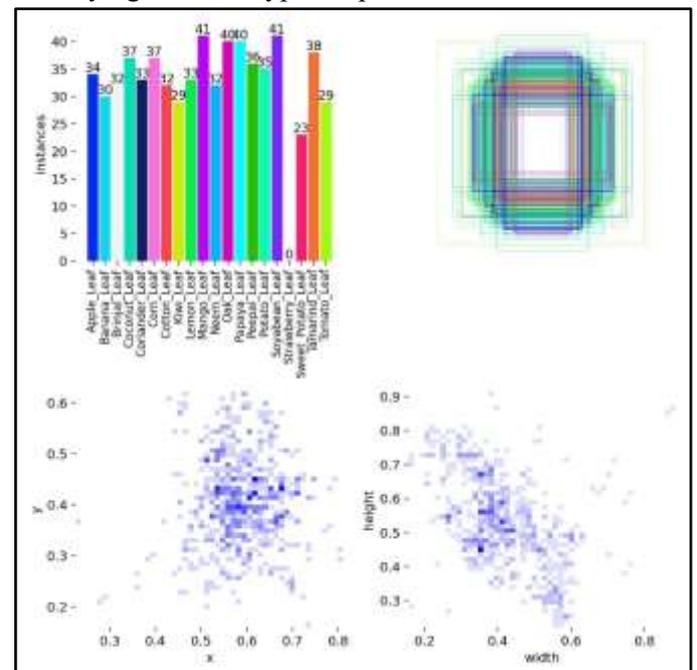


Fig 4: Labels Summary Plot and Dataset Correlation Plot

The figure represents the Labels Summary Plot and Dataset Correlogram used to analyze the plant leaf dataset before training the detection model. The diagram contains multiple visualizations that describe the distribution and characteristics of the labeled data. The first graph shows the training distribution of different plant leaf classes, indicating how many samples are available for each type of leaf used in the dataset. This helps in understanding whether the dataset is balanced across all classes. The colored rainbow box plots represent the distribution of bounding boxes for the detected leaf objects. These plots show how the labeled leaf regions vary in size and location across the dataset. Additionally, the diagram includes scatter plots showing the width and height of the bounding boxes, which help analyze the size variation of leaves within the images. Another scatter plot represents the x and y coordinates of the bounding boxes, indicating the spatial distribution of leaf objects within the dataset images. Overall, this visualization provides important insights into the dataset structure and ensures that the dataset is suitable for training the plant leaf detection model effectively.



Fig 5: Detection and Classification

The above figure shows the output results of the trained leaf detection model applied to different plant leaf images. The system successfully detects and classifies various types of leaves such as Sweet Potato Leaf and Potato Leaf. Each detected leaf is highlighted using bounding boxes with labels showing the predicted class name along with the confidence score. The confidence values such as 0.9 and 1.0 indicate the probability with which the model predicts the leaf class. The results

demonstrate that the proposed model is capable of accurately identifying and localizing different leaf types from the input images. The bounding boxes clearly outline the leaf region detected by the model, showing the effectiveness of the detection algorithm.

5. CONCLUSIONS

In the realm of AI, deep learning is included. Both academics and businesses have taken an interest in artificial intelligence and feature extraction due to its many useful applications. Numerous applications in the domains of image processing, natural language processing, and speech recognition have heavily utilized it. At the same time, it has become a leading institution for studies concerning agricultural plant protection, such as identifying plant diseases, evaluating pest ranges, and more. To improve research efficiency and the rate of technological change, to make plant disease feature extraction more objective, and to limit the downsides of artificial selection of disease spot features, deep learning is used for plant disease recognition. This article summarizes the recent progress that deep learning has made in detecting agricultural leaf diseases. This study discusses the current trends and concerns in plant leaf disease using the deep learning and sophisticated imaging techniques of CenterNet ResNET. identification. This approach should be valuable for researchers who are interested in identifying pest insects and plant illnesses. At the same time, we dealt with a number of critical issues that must be addressed right now.

Future research can focus on improving the proposed plant disease detection framework by incorporating larger and more diverse datasets covering different crop species, disease stages, and environmental conditions. Advanced deep learning models such as vision transformers and hybrid CNN-attention architectures can be explored to enhance feature extraction and localization accuracy. The system can be extended to real-time field deployment using mobile and edge-based platforms for on-site disease diagnosis. Integration with IoT sensors and weather data can enable early disease prediction and preventive decision support for farmers. Additionally, explainable AI techniques can be adopted to improve model transparency and trust, supporting practical adoption in precision agriculture.

REFERENCES

- [1] M. H. Saleem, J. Potgieter and K. M. Arif, "A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand," in *IEEE Access*, vol. 10, pp. 89798-89822, 2022, doi: 10.1109/ACCESS.2022.3201104.
- [2] M. B. Priya, M. N. Babu, M. Subhani and S. Chilaka, "Detection of Apple Plant Diseases using Leaf Images through Convolution Neural Networks," 2024 IEEE 1st International Conference on Green Industrial Electronics and Sustainable Technologies (GIEST), Imphal, India, 2024, pp. 1-6, doi: 10.1109/GIEST62955.2024.10959757.
- [3] E. Moupojou et al., "FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning," in *IEEE Access*, vol. 11, pp. 35398-35410, 2023, doi: 10.1109/ACCESS.2023.3263042.
- [4] K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Vrochidou and G. A. Papakostas, "Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern," in *IEEE Access*, vol. 11, pp. 62307-62317, 2023, doi: 10.1109/ACCESS.2023.3286730.
- [5] C. Madhurya and E. A. Jubilson, "YR2S: Efficient Deep Learning Technique for Detecting and Classifying Plant Leaf Diseases," in *IEEE Access*, vol. 12, pp. 3790-3804, 2024, doi: 10.1109/ACCESS.2023.3343450.
- [6] M. H. Asad, S. Saleem and A. Bais, "Detection and Mapping of Kochia Plants and Patches Using High-Resolution Ground Imagery and Satellite Data: Application of Machine Learning," in *IEEE Access*, vol. 11, pp. 92298-92311, 2023, doi: 10.1109/ACCESS.2023.3308909.
- [7] N. Nigar, H. M. Faisal, M. Umer, O. Okidi, and J. M. Lukose, "Improving Plant Disease Classification With Deep-Learning-Based Prediction Model Using Explainable Artificial Intelligence," *IEEE Access*, vol. 12, pp. 100005-100014, 2024, doi: 10.1109/ACCESS.2024.3428553.
- [8] M. A. Mohammed et al., "Edge-Cloud Remote Sensing Data-Based Plant Disease Detection Using Deep Neural Networks With Transfer Learning," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 11219-11231, 2024, doi: 10.1109/JSTARS.2024.3410515.
- [9] E. A. Al-Shahari, G. Aldehim, M. Aljebreen, J. Saad Alqurni, A. S. Salama and S. Abdelbagi, "Internet of Things Assisted Plant Disease Detection and Crop Management Using Deep Learning for Sustainable Agriculture," in *IEEE Access*, vol. 13, pp. 3512-3520, 2025, doi: 10.1109/ACCESS.2024.3397619.
- [10] R. Rashid, W. Aslam, R. Aziz and G. Aldehim, "An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models," in *IEEE Access*, vol. 12, pp. 23149-23162, 2024, doi: 10.1109/ACCESS.2024.3357099.
- [11] D. S. Joseph, P. M. Pawar and K. Chakradeo, "Real-Time Plant Disease Dataset Development and Detection of Plant Disease Using Deep Learning," in *IEEE Access*, vol. 12, pp. 16310-16333, 2024, doi: 10.1109/ACCESS.2024.3358333.
- [12] M. Pajany, S. Venkatraman, U. Sakthi, M. Sujatha and M. K. Ishak, "Optimal Fuzzy Deep Neural Networks-Based Plant Disease Detection and Classification on UAV-Based Remote Sensed Data," in *IEEE Access*, vol. 12, pp. 162131-162144, 2024, doi: 10.1109/ACCESS.2024.3488751.
- [13] A. Shrotriya, A. Kumar Sharma, A. Kumar Bairwa and R. Manoj, "Hybrid Ensemble Learning With CNN and RNN for Multimodal Cotton Plant Disease Detection," in *IEEE Access*, vol. 12, pp. 198028-198045, 2024, doi: 10.1109/ACCESS.2024.3515843.
- [14] O. Kundacina, V. Vincan, G. Gojic, V. Ninkovic and D. Miskovic, "Conformal Anomaly Detection for Predictive Maintenance in Thermal Power Plants," in *IEEE Access*, vol. 13, pp. 39738-39752, 2025, doi: 10.1109/ACCESS.2025.3546451.
- [15] B. Ramana Reddy, G. Kalnoor, M. Devashish and P. Sai Karthik Reddy, "Deep Learning Based Mobile Application for Automated Plant Disease Detection," in *IEEE Access*, vol. 13, pp. 107917-107925, 2025, doi: 10.1109/ACCESS.2025.3581099.