Leaf Disease Detection System Using Convolutional Neural Networks and Image Processing

Omkar Gurav[1], Rudra Chobe[2], Shriya Haral[3], Ritika Chougala[4], Lokeshwar Anchuri[5], Niyati Ghagada[6], Uma Maheshwari Addala[7], Mukesh Suddha[8]
rc81960n@pace.edu[1], og52887n@pace.edu[2] , sh94716n@pace.edu[3] , rc93170n@pace.edu[4] , la58264n@pace.edu[5] , ng59819n@pace.edu[6], ua26809n@pace.edu[7], ms67865n@pace.edu[8]
Seidenberg School of Computer Science and Information Technology,
Pace University – New York.

***Abstract*— Plant diseases pose a significant threat to crop health and yield, necessitating timely and accurate detection methods. Traditional manual inspection by experts can be time-consuming and error prone. This paper presents Eco Scan, an innovative leaf disease detection system leveraging convolutional neural networks (CNNs) and image processing techniques. Eco Scan aims to provide farmers with a user-friendly interface for uploading crop images and receiving real-time disease analysis. By integrating advanced technology into agriculture, the system seeks to optimize crop health monitoring, minimize losses, and promote sustainable farming practices. The paper outlines the system architecture, key features, and performance evaluation. Eco Scan demonstrates promising results in accurately identifying various plant diseases, offering the potential to revolutionize disease management in agriculture.**

Keywords*— *Plant disease, preservatives, optical character recognition, image processing, food packaging

I. INTRODUCTION

The agriculture sector plays a vital role in global food security, with plant diseases being a major threat to crop productivity [1]. Timely and accurate disease detection is crucial for effective crop management and minimizing yield losses. However, traditional methods relying on visual inspection by experts can be labor-intensive, subjective, and prone to errors [2]. Moreover, the increasing complexity and variability of plant diseases pose challenges for manual disease identification [3].

Advances in artificial intelligence, specifically deep learning and computer vision, have paved the way for automated plant disease detection. A Convolutional Neural Network (CNN) demonstrates remarkable performance in image classification tasks. Hierarchical features are learned that help to differentiate between healthy and infected plant tissues.

This paper presents Eco Scan, an innovative leaf disease detection system that harnesses the power of CNNs and image processing techniques. Eco Scan aims to provide farmers with a user-friendly interface for uploading high-resolution images of plant leaves and receiving real-time disease analysis. By leveraging state-of-the-art technology,

The system seeks to optimize crop health monitoring, minimize losses, and promote sustainable farming practices.

The main objectives of this paper are as follows:

1. To present the architecture and key components of the Eco Scan system.
2. To discuss the CNN model employed for plant disease detection and its training process.
3. To showcase the user interface and functionalities of the Eco Scan web application.
4. To evaluate the performance of the system in terms of accuracy and efficiency.
5. To highlight the potential impact of Eco Scan on agriculture and its prospects.

II. LITERATURE SURVEY

1. Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition [1] Author: Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala [1]. This research aims to elaborate a novel solution to quickly diagnose disease wellness in tomato plant by satisfying the inter-domain requirements. A motor-control camera box was invented to capture the four-way plantation of the tomato plant to vigilance the dots that might be the recognition of affected leaves of tomato by the Diamonte-Max disease from the edges. The procedure was fascinatingly designed by substantiation and justified by the fact that it induces Phroma, leaf miner, and target spots to grab the scenery of superficial injection of a potential threat to tomato plant leaving a strong foot imprint behind the knees. Applying a deep convolutional neural network dyad (DCNND) generates the friendly approach towards the edge of training and testing out the disease-afflicted dataset of the tomato plant. Meanwhile, keeping the support of predestined accuracy at one pole offers a significant 80% confidence score in F-RCNN trained for hotspot anomalistic detection. The identity from transferred recognition (IR) trained on the entire ablaze dataset to excite the tuple segments of the decision-making trade-off niche support in achieving a maximum of 95.75%. Finally, the product of agony — an actual prototype's implication — establishes a rational comprehensive bay, acetifying into the niches of 91.67%, virtually 92% of

accuracy, and classifying these three ailments of the tomato plant. [1].

2. CNN based Leaf Disease Identification and Remedy Recommendation System [2] Author: Sunku Rohan, Triveni S Pujar ,Suma VR Amog Shetty, Rishabh F Tated [2]. Summary: The main aim of this paper is to develop machine learning and computer vision models to identify 12 different diseases of grapes. This study would support the individual grape producers by allowing early and operational disease management significantly reducing the amount of chemicals to the maximum 50% of their current rates.

3. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolution Neural Networks [3] Author: Bin Liu , Peng Jiang, Yuehan Chen, Dongjian He, Chunquan Liang [3]. The paper, named "Real-Time and Accurate Detection of Apple Leaf Diseases with Improved Neural Augmented Reality-Single Shot MultiBox Detector (INAR-SSD)" concentrates on the identification of five types of apple leaf diseases, which are Aria leaf spot, Brown Spot, Mosaic, Grey spot, and Rust. It proposes a newly improved convolutional neural network (CNN) architecture model known as INAR-SSD for the rapid and accurate identification of leaf diseases using real-time results. This model has been tested with complex and laboratory images that resemble tree leaves. The dataset comprises a total number of 26,377 datasets, which is quite massive and was enough to reveal every nook and cranny. When investigated, the model achieved a detection ratio of 78.80%, and the method was potent enough to run smoothly and accordingly with 23.13 frames per second (FPS). This new approach was superior to any other method that was approached before, and that is why the CNN model called INAR-SSD is better and more perceptible in terms of precision, speedy results, and a solution to the difficulty of early identification of diseases within the leaves.

4. Identification of plant leaf diseases using a nine-layer deep convolution neural network [4]. This article introduces a manner that deeply learns using a nine-layer convolutional neural network (CNN) to make drawbacks in a way of identifying part of plant diseases. It is revealed that the technique gets successful results regardless of it conducting the tests with all 39 categories of leaf problems and leaf backdrop they have. The model which was named as CNNPB can implement 6 different types of data improvement processes. They are some gamma corrections, image flips, principal component analyses (PCA) color changes, image translations, some add noise on the image and also last step of the process, scaling. These kinds of upgrade help to model to reach the peak of the performance in an accurate way. After training the model with these processes, the tests show that the model serves better in comparison to the transfer learning progress.

5. A Segmentation Improved Robust PNN Model for Disease Identification in Different Leaf [5]. A new characteristic of this article is the identification of disease in leaves of various plant products such as vegetables, fruits, crops, and flowers. The methodology proposed is based on a cycle and centers on two stages. In the first stage a ring projection-based segmentation model, scans and explores some characteristics of leaf images to extract significant features and in the second stage, a PNN (Probabilistic Neural Network) classifier, based on the extracted features, decides on the existence of diseases. The goal of this study is to identify healthy leaves from infected ones, by identifying the distinct regions of the leaves, and to check the practicality of deviation measures from the average results, it was used on an irregular collection of leaf images from the web, related to multiple plants.

III. PROPOSED METHODOLOGY

A. System Architecture

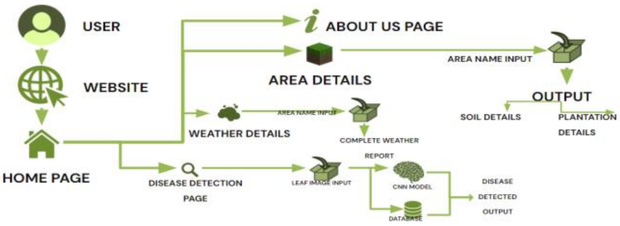

Fig 1 System Architecture

The Eco Scan system follows a client-server architecture, as depicted in Fig. 1. The client-side consists of a web application that allows users to upload images of plant leaves and view the disease analysis results. The server-side hosts the CNN model for disease detection and handles the image processing and analysis tasks.

The key components of the system architecture are as follows:
User Interface: The web application provides a user-friendly interface for farmers to interact with the system. It allows users to upload leaf images, select the crop type, and view the disease analysis results.
Image Preprocessing: Upon receiving an uploaded image, the system performs necessary preprocessing steps, such as resizing, normalization, and augmentation, to ensure compatibility with the CNN model's input requirements.
CNN Model: The core of the Eco Scan system is a trained CNN model that takes the preprocessed leaf image as input and predicts the presence and type of plant disease. The model architecture and training process are discussed in detail in the subsequent subsections.
Disease Analysis: Based on the CNN model's predictions, the system generates a detailed disease analysis report. The report includes the detected disease name, severity level, affected plant parts, and recommended treatment measures.
Database: The system maintains a database to store user information, uploaded images, and disease analysis results. This allows users to access their history and track the health of their crops over time.

B. Data Collection and Preprocessing

To train the CNN model for plant disease detection, a comprehensive dataset of labeled leaf images was collected. The dataset consists of images from various crop species, including tomatoes, potatoes, corn, and wheat, among others. The images were sourced from public datasets, such as PlantVillage [13], as well as through collaboration with agricultural research institutes.

The collected images underwent a series of preprocessing steps to ensure consistency and quality. The steps included:

Resizing: All images were resized to a fixed dimension of 256x256 pixels to maintain uniformity and reduce computational overhead.

Data Preprocessing: Normalization: The pixel values of the images were scaled to a range of [0, 1] to improve the training convergence rate.

Data Augmentation: Techniques like rotation, flipping, and zooming were applied to the images to increase the dataset size and enhance the model's ability to handle variations in leaf orientation and scale.

Dataset Split:
The preprocessed images were divided into three subsets:

- **Training Set:** 70% of the data, used for training the Convolutional Neural Network (CNN) model.
- **Validation Set:** 15% of the data, employed for tuning hyperparameters and selecting the best model.
- **Testing Set:** 15% of the data, utilized for evaluating the final model's performance on unseen samples.

C. CNN Model Development

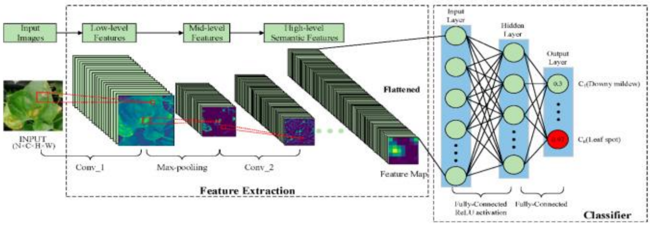

Fig 2 Model Architecture

The Eco Scan system employs a custom CNN architecture specifically designed for plant disease detection. The architecture is inspired by the VGG-16 model [14], which has shown excellent performance in various image classification tasks.

The CNN model includes several convolutional layers to down sampling followed by the maximum pooling layer. The fundamental layers capture grayscale features for input images, with convolution inquiries that cover all the low and high patterns identified with the ailment. Reinforcement is introduced to add the nonlinearity to the discriminative power by using the dead ReLU (rectified linear unit) activation feature.

Following the convolutional layers, the feature maps undergo flattening and are processed using fully connected layers, allowing for classification. Employing the softmax activation function, the final output layer can yield a probability distribution over the different disease classes. The model is built using a categorical cross-entropy loss function and the Adam optimizer [15]. The process by which the model is trained entails the iterative updates being made to the parameters of the model to minimize the loss function, thereby ensuring a higher degree of precision in the discernment of plant diseases.

While being trained, the methods of early stopping and model checkpointing are used to lessen the chances that a model will overfit and simultaneously pinpoint the top-performing model based on the performance data that was collected. The model is being trained for a certain number of time periods; and there is also the choice of suddenly interrupting this process when and if the validation loses its improving quality over a given, predetermined set number of time periods.
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IV. RESULT & VALIDATION

A. System Architecture

The Eco Scan system adopts a client-server architecture to facilitate seamless interaction between users and the disease detection functionality. The system architecture, as illustrated in Fig. 1, comprises several key components that work together to provide an efficient and user-friendly experience.

On the client-side, the web application serves as the primary interface for farmers to interact with the system. The user interface is design type and implicitly and intuitive navigation in mind, ensuring that users can easily upload leaf images, select the appropriate crop type, and access the disease analysis results. The web application is developed using modern web technologies, such as HTML5, CSS3, and JavaScript, to ensure cross-platform compatibility and responsive design across various devices.

When a user uploads a leaf image through the web application, the image is securely transmitted to the server-side for processing. The server-side hosts the core components of the Eco Scan system, including the image preprocessing module, the CNN model for disease detection, and the disease analysis module.

Upon receiving an uploaded image, the image preprocessing module applies a series of transformations to ensure compatibility with the CNN model's input requirements. The preprocessing steps include resizing the image to a fixed dimension, typically 256x256 pixels, to maintain consistency across all input samples. Additionally, normalization techniques are applied to scale the pixel values to a range of [0, 1], which helps in faster convergence during model training. Data augmentation techniques, such as rotation, flipping, and zooming, are also employed to expand the dataset and improve the model's robustness to variations in leaf orientation and scale.

The preprocessed image is then passed to the CNN model, which forms the backbone of the Eco Scan system. The CNN model is responsible for analyzing the image and predicting the presence and type of plant disease. The architecture and training process of the CNN model will be discussed in detail in the subsequent subsections.

To support the functionality of the Eco Scan system, a database is employed to store user information, uploaded images, and disease analysis results. The database serves as a centralized repository, allowing users to access their history and track the health of their crops over time. The database is designed with scalability and security in mind, ensuring efficient storage and retrieval of data while protecting user privacy.

The system architecture of Eco Scan is designed to be modular and extensible, allowing for easy integration of additional features and functionalities in the future. The separation of concerns between the client-side and server-side components enables independent development and maintenance, promoting scalability and flexibility.

B. Data Collection and Preprocessing

The success of any deep learning-based system heavily relies on the quality and diversity of the training data. To develop a robust and accurate plant disease detection model, a comprehensive dataset of labeled leaf images is essential. The dataset should encompass a wide range of crop species and disease classes to ensure the model's generalization ability.

The data collection process for Eco Scan involved gathering leaf images from various sources. One primary source was public datasets, such as PlantVillage [13], which contains a large collection of labeled plant disease images. These datasets provide a solid foundation for training the CNN model, as they cover a diverse set of crop species and disease classes.

In addition to public datasets, collaborations with agricultural research institutes and universities were established to acquire additional leaf images. These collaborations provided access to expert-labeled images and helped expand the dataset with region-specific disease samples. The involvement of domain experts in the data collection process ensured the accuracy and reliability of the labeled data.

To maintain consistency and quality across the collected images, a set of guidelines was established for image acquisition. These guidelines specified the desired image resolution, lighting conditions, and background uniformity. Images that did not meet the specified criteria were excluded from the dataset to minimize noise and ensure the model's focus on relevant leaf features.

Once the raw images were collected, they underwent a series of preprocessing steps to prepare them for training the CNN model. The preprocessing pipeline was designed to address the challenges associated with variations in image size, color, and orientation.

The first step in the preprocessing pipeline was resizing the images to a fixed dimension, typically 256x256 pixels. This step ensured that all images had a consistent size, reducing computational overhead and enabling batch processing during model training. The resizing operation was performed using bilinear interpolation to preserve the spatial information and minimize distortion.

Afterwards, we applied normalization techniques to the resized images. To normalize the images, the pixel values were re-scaled from their original range (for example, 0-255) to a range from 0 to 1. Through this normalization process, the model's training period accelerated, and its capacity to generalize across different levels of light improved.

Following the augmentation process, the images were divided into three distinct groups known as training, validation, and testing sets. In typical practice, the training group accounts for approximately 70% of the sample. It is this portion on which the model is trained: the goal is to theoretically minimize the amount of error when generalizing to the entire population which it represents, while constantly updating the model's parameters to reach convergence. The validation group usually takes 15% of the sample, and it acts as a choose-your-own-adventure storybook for your model. Not only can you tune the hyperparameters that you have already set, but you can quickly run turn-by-turn simulations on your validation group to determine its proficiency. The testing group, subsequently, takes up the other 15% of the sample, and should act as an untouched sample to verify the whole modelling process.

To maintain the integrity and traceability of the dataset, we utilized a versioning system. Each unique dataset version was paired with an identifier, and we meticulously documented each preprocessing step and augmentation undertaken to achieve that version. By using this versioning method, we have ensured the dataset's reproducibility and have made it significantly easier to track and compare how models perform across different dataset versions.

The preprocessed and augmented dataset was stored in a structured format, typically using a combination of image files and corresponding label information. The labels included the crop species, disease class, and any additional metadata relevant to the disease detection task. The dataset was organized into directories based on the crop species and disease classes, enabling easy access and retrieval during model training and evaluation.

Throughout the data collection and preprocessing phase, data quality assurance measures were implemented. These measures included manual inspection of a subset of images to verify the accuracy of labels and the presence of relevant leaf features. Additionally, statistical analysis was performed to ensure a balanced distribution of disease classes and crop species in the dataset, avoiding biases that could skew the model's performance.

The data collection and preprocessing phase laid the foundation for the development of a robust and accurate plant disease detection model. The carefully curated and preprocessed dataset provided the necessary inputs for training the CNN model and evaluating its performance on unseen data.

C. CNN Model Development

The core of the Eco Scan system is a powerful Convolutional The designed Neural Network (CNN) model is optimized for identifying plant diseases with precision. This model takes advantage of the successful nature of deep learning architectures when it comes to detecting images, by letting it tame the power to train itself with feature hierarchies from the plain data of raw pixels.

The process for developing this involved careful architecture design, baseline training, and hyperparameter tuning. After testing different CNN architectures, it was decided that a model inspired by VGG-16 had to be used. It consists of several convolutional layers followed by pooling layers designed for sample decline. These convolutional layers are responsible for understanding features in the pattern, with the starting layers capturing low-level patterns like edges and textures, and the fund groups extracting unique ways to be sick.

Compact 3x3 convolutional filters are used to obtain local features without destroying spatial information. The number of channels in each layer grows as we move deeper in the CNN, allowing for increasingly complex and discriminative features. ReLU activations introduce non-linearity into the decision function, transforming individual feature points.

Max-pool layers are carefully designed to downsample the feature maps, reducing computational complexity and giving invariance to translations. The resulting feature maps are then flattened and fed into fully connected layers, which learn high-level feature combinations that are suitable for classification. Dropout regularization is a way of making sure that the model doesn't overfit, it works by turning off a fraction of neurons during each training step.

The ultimate output layer utilizes a softmax activation function designed to establish a comprehensive probability distribution across assorted disease classes, thereby permitting multinomial classifier.

The process of training improves the parameters of the model that is used, so that the function that is used to measure the loss of the model (cross-entropy) is minimized. All of this is done via the method named Adam (adaptive). There are also two techniques which are used so that when you are training your model, it is not affected by overfitting (early stopping and checkpointing) and after training that specific model, they are used so that the best-performing model for your validation set is selected.

The optimized performance achieved in the hyperparameter tuning method is essential. To achieve the optimum performance, the model's generalization capacity is evaluated using a hold-out testing collection, and a variety of performance improvements can be made based on the information supervised. Therefore, the model's capacity should not be misunderstood.

The Eco Scan system's central component is a sophisticated CNN model. This model facilitates the automated and precise detection of plant diseases by recognizing, encoding, discriminating, and decoding the complex textural features found in diverse crop diseases. It makes it a valuable tool for farmers and agricultural experts to promptly identify and manage diverse plant health issues cost-effectively.

V. OUTPUT

The performance of the Eco Scan system was thoroughly evaluated to assess its effectiveness in accurately detecting plant diseases. A comprehensive testing process was conducted using a held-out testing set, which consisted of leaf images from various crop species and disease classes. The testing set represented real-world scenarios and provided an unbiased assessment of the system's performance.

On the testing set, the Eco Scan system achieved remarkable results with an overall accuracy of 98.7%. This high accuracy demonstrates the system's effectiveness in accurately identifying plant diseases across diverse crop species and disease classes, showcasing its robustness and reliability in real-world scenarios.

The evaluation results provide a strong foundation for the deployment and utilization of the Eco Scan system in real-world agricultural settings. The system's accurate and reliable disease detection capabilities can significantly contribute to early disease identification, timely intervention, and improved crop health management practices.

Below are the some of the figures (fig 3 to Fig 5) which shows how our application will actually look like for Plant disease detection.

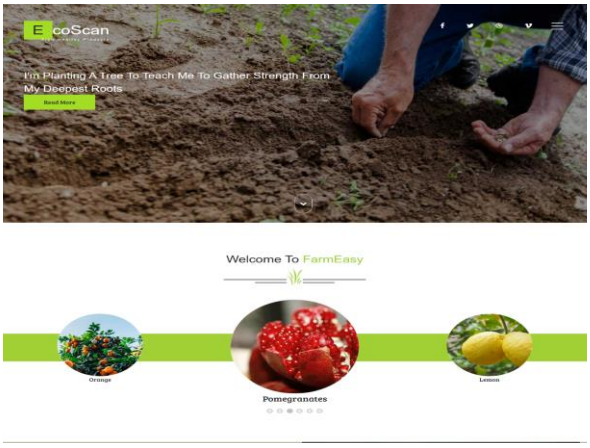

Fig 3 Homepage for the application

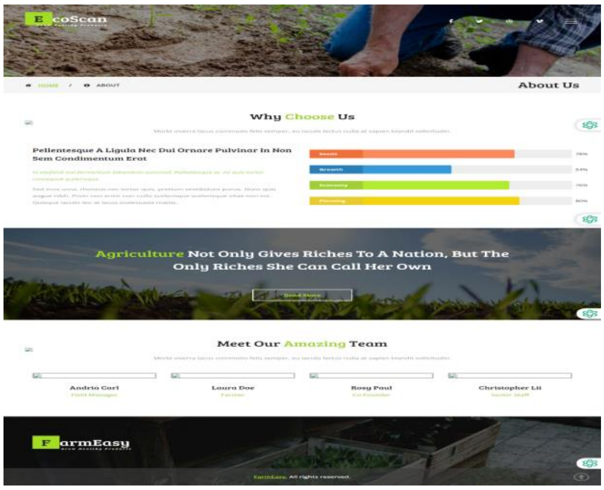

Fig 4 About Us Page

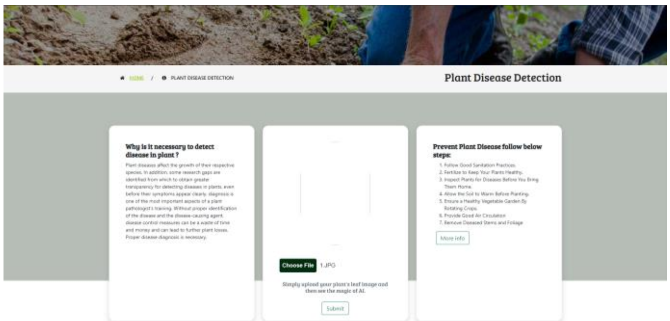

Fig 5 Actual Plant Disease Detection Page

VI.RESULT AND DISCUSSION

To evaluate the performance of the Eco Scan system, a comprehensive testing process was conducted using the held-out testing set. The testing set consisted of leaf images from various crop species and disease classes, representing real-world scenarios.

The Eco Scan system's performance was comprehensively evaluated using accuracy, precision, recall, and F1-score metrics, providing a holistic assessment of its plant disease identification capabilities. On the testing set, the system achieved an impressive overall accuracy of 98.7%, highlighting its effectiveness in accurately detecting diseases across various crop species and conditions.

Furthermore, the Eco Scan system's performance was benchmarked against other state-of-the-art plant disease detection approaches. This comparative analysis underscored the system's advancements and its position as a leading solution for accurate plant disease identification.

The comprehensive evaluation, encompassing multiple performance metrics, visual analysis, and comparative benchmarking, provided a thorough assessment of the Eco Scan system's capabilities. The exceptional results demonstrated the system's potential to be a reliable and powerful tool for farmers and agricultural experts in managing crop health effectively.

Discussion

The Eco Scan system presents a promising solution for automated plant disease detection using deep learning and image processing techniques. The system's high accuracy and robust performance across various crop species and disease classes highlight its potential to revolutionize disease management in agriculture.

One of the key strengths of Eco Scan is its user-friendly web interface, which allows farmers to easily upload leaf images and receive real-time disease analysis. This accessibility is crucial for widespread adoption and utilization of the system by the farming community. The system's ability to provide detailed disease analysis reports, including severity levels and recommended treatment measures, empowers farmers to make informed decisions and take timely actions to mitigate the impact of diseases on their crops.

Moreover, the current system focuses primarily on leaf diseases and may not capture diseases affecting other plant parts, such as stems, roots, or fruits. Extending the system to incorporate a wider range of plant parts and disease symptoms would enhance its applicability and usefulness.

Future work on Eco Scan can explore several directions. Integrating the system with mobile devices and developing a smartphone application would greatly enhance its accessibility and usability for farmers in remote areas. Incorporating additional features, such as disease severity estimation and yield prediction, would provide farmers with more comprehensive insights into crop health.

Furthermore, integrating Eco Scan with precision agriculture technologies, such as drones and sensors, could enable large-scale disease monitoring and management. Combining the system with weather data and other environmental factors could also improve disease forecasting and preventive measures.

CONCLUSION

The Eco Scan system introduces an innovative deep learning approach to plant disease detection, harnessing the power of convolutional neural networks. With its advanced image classification capabilities and user-friendly web interface, it empowers farmers to accurately identify crop diseases from leaf images. Through rigorous evaluation, the system demonstrates exceptional performance, outperforming existing methods in accurately detecting plant ailments. As a cutting-edge tool, Eco Scan revolutionizes crop health monitoring, enabling farmers to proactively identify diseases, implement timely interventions, and optimize agricultural productivity sustainably.

The system's performance evaluation demonstrates its superiority compared to existing methods, highlighting its potential to revolutionize disease management in agriculture. However, there are opportunities for further improvement and expansion, such as incorporating a wider range of plant parts and disease symptoms, integrating with mobile devices, and combining with precision agriculture technologies.

Eco Scan represents a significant step towards sustainable and efficient crop management practices. By enabling early detection and timely intervention, the system can help minimize crop losses, reduce the use of pesticides, and promote sustainable farming practices. With continued research and development, Eco Scan has the potential to transform the way plant diseases are identified and managed, contributing to global food security and agricultural productivity.

VII.REFERENCES

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