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AgroBot: AI-based Leaf Disease Detection with Intelligent Chatbot

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Abstract*— Agriculture plays a vital role in global food production; however, plant diseases significantly reduce crop yield and quality, posing a major challenge for farmers. Early detection of leaf diseases is difficult due to limited access to expert knowledge and timely diagnosis. To address this problem, this paper proposes AgroBot, an AI-driven leaf-disease detection system integrated with an intelligent chatbot to provide smart agricultural assistance. The system allows users to upload leaf images through a web-based interface, which are then processed using Deep Learning techniques. A ResNet model, specifically based on the Residual Network architecture, is employed for accurate disease classification. To mitigate dataset imbalance and improve model generalization, a Generative Adversarial Network (GAN) is used to augment the data by generating realistic synthetic leaf images. The model is trained and evaluated on the PlantVillage dataset, consisting of diverse crop leaf images under varying conditions. Experimental results demonstrate that the proposed system achieves an accuracy of approximately 95–98% in disease classification, showing robustness even under noisy and imbalanced data scenarios. In addition to detecting diseases, the system provides severity analysis, along with tailored treatment recommendations and preventive measures. Furthermore, AgroBot integrates an intelligent chatbot that delivers real-time, context-aware guidance to farmers, assisting them in understanding disease symptoms, suggesting remedies, and recommending relevant government agricultural schemes and support services. This enhances accessibility to critical agricultural knowledge and promotes informed decision-making. The proposed system demonstrates significant potential in advancing precision agriculture, improving crop health management, and supporting farmers with scalable, technology-driven solutions.

***Keywords*— Leaf Disease Detection, Residual Neural Network, Generative Adversarial Network, Data Augmentation, Intelligent Chatbot, Smart Agriculture, Precision Farming.**

I. INTRODUCTION

Agriculture plays a key role in global food security and economic development, especially in developing countries where many people rely on farming for their livelihood. However, plant diseases significantly lower crop yield, quality, and profitability, causing large economic losses every year.

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Detecting and accurately diagnosing leaf diseases is essential for reducing damage. Yet, traditional methods depend on expert knowledge, manual inspections, and laboratory analysis, which are time-consuming, costly, and not always accessible to small-scale farmers.

Recent progress in Artificial Intelligence (AI) and Deep Learning has introduced new options for automating plant disease detection through image analysis. Convolutional Neural Network have performed well in image classification tasks, including identifying agricultural diseases. However, many current systems have limitations, such as uneven datasets, poor performance in noisy conditions, and a lack of practical advice. To address these issues, advanced methods like Generative Adversarial Networks (GANs) can be used to enhance data by creating realistic synthetic images, which improve model accuracy and robustness.

We propose AgroBot, an AI-based system designed for leaf disease detection and advisory support in smart and precision agriculture.

This system combines ResNet-based disease classification with GAN-based data augmentation to improve detection accuracy and reliability. In addition to identifying diseases, AgroBot offers severity assessment, treatment recommendations, preventive advice, and interactive support through an intelligent chatbot. By integrating automated diagnosis with actionable insights and a user-friendly web interface, the proposed framework aims to provide a comprehensive and scalable solution to support farmer decision-making.

The article introduces AgroBot, an AI-based chatbot that provides prevention and treatment advice based on disease name and severity.

Section I explains the motivation, objectives, and importance of AI-based leaf disease detection in modern agriculture. Section II provides a review of existing plant disease detection methods, deep learning approaches, and intelligent advisory systems, highlighting the research gaps this work addresses. Section III describes the proposed methodology, including system architecture, GAN-based data augmentation, ResNet-based disease classification, severity analysis, and chatbot integration. Section IV presents a feasibility study, analyzing the technical, operational, and economic viability of implementing AgroBot in real-world agriculture settings. Section V discusses experimental results, system performance, and practical implications of the proposed approach, demonstrating AgroBot's effectiveness and applicability in smart and precision agriculture. Section VI shows that Residual Neural Network are the best for disease predictions. Section VII justifies the prevention functionality, Section VIII gives updates, and Section IX specifies impact and ethical deployment.

II. Literature Review

Recent advancements in plant disease detection systems focus on improving classification accuracy and addressing data imbalance issues. GAN-enhanced deep learning frameworks have demonstrated the ability to generate realistic synthetic leaf images, which improve class balance and overall model performance [1]. Hybrid dilated Convolutional Neural Networks combined with attention mechanisms further enhance detection performance by allowing models to focus on infection-prone areas of leaves, improving feature extraction and classification accuracy [2]. Research on AI-driven precision agriculture systems highlights the integration of disease detection with intelligent advisory and analytical frameworks to support farmers in making informed decisions [3]. Complementing detection models, intelligent chatbot systems have been introduced to convert diagnostic outputs into user-friendly recommendations, making it easier for farmers with limited technical knowledge to understand and act on the results [4]. Further developments in smart agriculture highlight the importance of scalable and deployable architectures.

Reviews of AI-based smart farming technologies emphasize the value of combining computer vision, IoT systems, and knowledge-based decision engines to create comprehensive digital farming ecosystems [5]. Emerging comparisons between Vision Transformers and CNN-based models show potential improvements in high-resolution image analysis, expanding possibilities for plant disease recognition [6]. IoT-enabled real-time detection frameworks have shown how integrating field-level image acquisition with cloud-based CNN inference can support scalable and efficient disease monitoring systems [7]. Additionally, advances in disease severity estimation models go beyond simple classification by quantifying infection intensity, offering more detailed and actionable diagnostic outputs [8]. Data augmentation techniques have received considerable attention in recent years. Conditional GAN frameworks have been successfully used to address class imbalance by generating synthetic samples that enrich underrepresented categories, leading to improved model robustness and predictive accuracy [9]. Similar augmentation-based approaches have shown that synthetic data generation enhances CNN stability and reduces overfitting, particularly in limited dataset environments [10].

Ensemble deep learning techniques further strengthen classification performance by combining multiple models to reduce variance and improve reliability across different plant species and disease types [11]. Domain-specific

CNN optimization strategies tailored for particular crops demonstrate the importance of preprocessing and architecture customization in achieving higher diagnostic accuracy [12]. Comparative analyses of CNN architectures provide valuable insights into model depth, parameter tuning, and preprocessing methods suitable for agricultural imagery [13]. Foundational research on data augmentation and deep learning methodologies has significantly influenced plant disease detection systems. Comprehensive surveys on image augmentation highlight various transformation and adversarial generation techniques that enhance CNN generalization capability [14]. Empirical evaluations confirm that deep CNN models outperform conventional machine learning algorithms in crop disease recognition, establishing deep learning as the standard approach in agricultural image analysis [15]

III. METHODOLOGY

The proposed AgroBot system follows a modular and systematic methodology to enable accurate leaf disease detection and intelligent agricultural advisory services. The methodology is divided into distinct phases, including data collection, image preprocessing, GAN-based data augmentation, ResNet model training, disease severity analysis, recommendation generation, and chatbot-based user interaction. This structured approach ensures robustness, scalability, and practical applicability in real-world agricultural environments. Users upload plant leaf images via a user-friendly interface, which are preprocessed using resizing, normalization, and noise removal techniques. During the training phase, a Generative Adversarial Network (GAN) is employed to generate realistic synthetic leaf images for data augmentation, addressing dataset imbalance and improving model generalization. The augmented dataset is used to train a ResNet Model that extracts discriminative features and classifies plant diseases. In the prediction phase, the trained CNN analyses the input image to identify the disease and estimate its severity level.

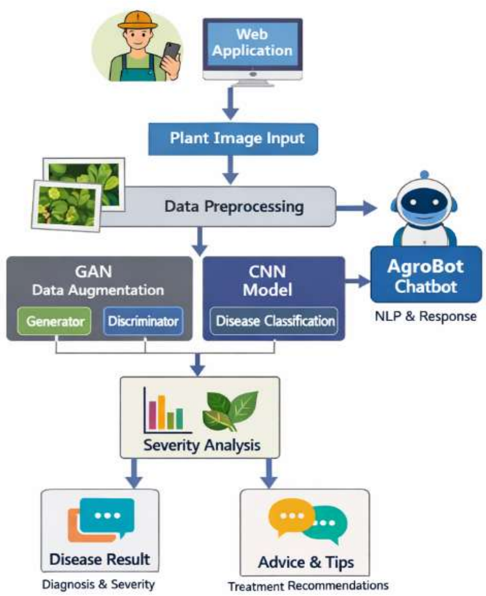

Fig 1. Overall architecture of the proposed AgroBot System

A. Dataset Description

In this study, the PlantVillage dataset is utilized for training and evaluating the proposed AgroBot system. This dataset is widely used in plant disease detection research due to its diversity and well-labeled image collection. It contains images of healthy and diseased plant leaves across multiple crop species, captured under controlled conditions.

The dataset comprises a large number of high-resolution leaf images categorized into various disease classes. Each image is annotated with its corresponding label, enabling supervised learning for classification tasks. For experimental purposes, the dataset is divided into two subsets: 80% of the images are used for training the model, while the remaining 20% are reserved for testing and validation. This division ensures that the model is evaluated on unseen data, thereby assessing its generalization capability.

TABLE I: PLANTVILLAGE DATASET DESCRIPTION

Parameter	Details
Dataset Name	PlantVillage
Source	Publicly available (Kaggle)
Total Images	54,306
Number of Classes	38 (Healthy and Diseased Leaves)
Image Type	RGB Leaf Images
Data Split	80% Training / 20% Testing
Training Samples	43,445
Testing Samples	10,861
Preprocessing	Image resizing, normalization
Augmentation	GAN-based synthetic image generation

B. Image Preprocessing

Prior to model training, all input images undergo preprocessing to improve data quality and ensure uniformity. The images are resized to a fixed resolution suitable for the model input. Pixel values are normalized to a standard range, which helps in faster convergence during training. To enhance model robustness, data augmentation techniques such as rotation, flipping, and scaling are applied. Additionally, a Generative Adversarial Network (GAN) is utilized to generate synthetic images, increasing dataset diversity and reducing overfitting. This step improves the generalization capability of the model when exposed to real-world conditions.

C. GAN-based Data Augmentation

To address dataset imbalance and improve model generalization, a Generative Adversarial Network (GAN) is employed during the training phase. The GAN consists of a Generator that creates synthetic plant leaf images and a Discriminator that differentiates between real and generated images. Through adversarial training, the Generator learns to produce realistic synthetic images that closely resemble real diseased leaves. These synthetic images are combined with the original dataset to form an augmented and balanced training dataset, enhancing the robustness of the ResNet model.

D. ResNet-Based Disease Classification

The preprocessed images are fed into a deep learning model based on a Residual Network (ResNet). The ResNet architecture is chosen due to its ability to effectively train deep neural networks using residual connections, which help overcome the vanishing gradient problem. The model performs feature extraction and classification in a unified framework. Initially, convolutional layers extract low-level features such as edges and textures. As the network depth increases, higher-level features representing disease patterns are captured. The residual connections enable efficient information flow across layers, improving learning capability. The extracted features are then passed through fully connected layers, where the model classifies the input image into specific disease categories.

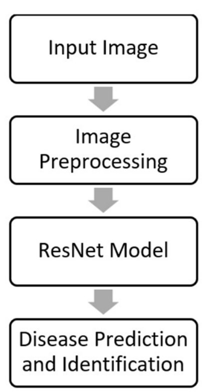

Fig 2. ResNet-based feature extraction and disease classification process

E. Disease Severity Analysis

In addition to disease classification, the proposed system includes a severity estimation module. This module analyzes the proportion of the infected region in the leaf image relative to the total leaf area. Based on this analysis, the disease is categorized into different severity levels such as mild, moderate, and severe.

This functionality provides more detailed insights to users, enabling better decision-making for crop management and treatment.

F. Model Traning and Evaluation

The model is trained using the cross-entropy loss function, which measures the difference between predicted and actual class labels. During training, the model parameters are optimized iteratively to minimize this loss.
To evaluate the performance of the proposed system, standard metrics such as accuracy, precision, recall, and F1-score are used. These metrics provide a comprehensive assessment of the model's effectiveness in disease classification.

G. System Output and User Interaction

The final output of the AgroBot system includes the predicted disease name, confidence score, and severity level. Additionally, the system provides recommendations and treatment suggestions through an integrated chatbot interface. This user-friendly design ensures that farmers and users can easily interpret the results and take appropriate actions for disease management.

H. Recommendation and Knowledge Base Integration

Based on the detected disease and severity level, the system retrieves appropriate treatment and prevention recommendations from an integrated knowledge base. The knowledge base stores structured information related to disease symptoms, control measures, pesticide usage, and best agricultural practices. Additionally, it contains details of relevant government agricultural schemes, insurance programs, and farmer support services. This enables AgroBot to provide actionable and context-aware guidance beyond disease identification.

I. Intelligent Chatbot Module

An intelligent chatbot is integrated into the system to enhance user interaction and accessibility. The chatbot utilizes Natural Language Processing (NLP) techniques to understand user queries related to plant care, fertilizers, pesticides, disease management, and government scheme eligibility. By accessing the knowledge base, the chatbot delivers instant and accurate responses, making the system user-friendly and farmer-centric.

J. System Deployment and Workflow

The AgroBot system is deployed as a web-based application that integrates the frontend user interface, backend processing, deep learning models, chatbot services, and database. Users upload plant leaf images through the interface, and the system processes the input through the trained ResNet model. The final output includes the detected disease name, severity level, treatment recommendations, and scheme guidance, all delivered in a clear and accessible format.

IV. FEASIBILITY STUDY

The feasibility study evaluates the practicality of implementing the proposed AgroBot system in real-world agricultural environments. The analysis is conducted across dimensions to assess whether the system can be effectively developed, deployed, and used by farmers and agricultural stakeholders.

A. Technical Feasibility

The AgroBot system is technically feasible, relying on widely available technologies. ResNet and GAN models can be implemented using open-source frameworks like TensorFlow, while image preprocessing, chatbot integration, and database management can be handled with standard web technologies. The system can be trained and deployed using standard computing resources without requiring specialized hardware.

B. Economic Feasibility

The proposed system is economically viable because it uses open-source software and publicly accessible datasets, which significantly lowers development and deployment costs. The use of cloud infrastructure allows for flexible resource allocation based on demand, reducing operational expenses. By enabling early disease detection and timely intervention, AgroBot can help minimize crop losses and reduce the unnecessary use of pesticides, offering long-term economic advantages to farmers.

C. Operational Feasibility

From an operational perspective, AgroBot is designed to be user-friendly and accessible to farmers with minimal technical expertise. The web-based interface allows users to easily upload plant leaf images and receive diagnostic results and recommendations. Since the system operates online, it can be accessed remotely without the need for complex installation procedures. This ensures smooth adoption and practical usage in agricultural settings.

D. Legal and Ethical Feasibility

The proposed AgroBot system complies with legal and ethical standards as it does not involve the collection of sensitive personal data. The plant images used for disease detection are voluntarily provided by users, and all data handling follows standard data privacy practices. The system relies on publicly available datasets and open-source tools, avoiding intellectual property violations. Ethically, AgroBot supports responsible pesticide usage by recommending treatment when necessary, thereby promoting environmentally friendly and sustainable farming practices.

E. Feasibility Conclusion

The AgroBot has the potential to assist farmers in early disease diagnosis, reduce crop loss, and promote smart and sustainable farming practices. Future enhancements may include mobile app deployment, real-time field monitoring, and integration with IoT sensors for precision agriculture. The proposed system is technically sound, cost-effective, user-friendly, and scalable, making it suitable for real-world agricultural applications.

V. Discussion

The experimental results demonstrate that the proposed ResNet-based model provides high accuracy in detecting plant leaf diseases. The improved performance can be attributed to the deep feature extraction capability of the residual network, which effectively captures complex patterns in leaf images. Additionally, the use of data augmentation techniques enhances the diversity of the training dataset, leading to better generalization. When compared with conventional convolutional neural network models, the proposed approach achieves superior classification accuracy and reduced error rates. Furthermore, the inclusion of a disease severity estimation module adds practical value by assisting users in understanding the extent of infection. However, the system may face challenges when applied to real-time images with varying environmental conditions such as lighting and background noise. Future enhancements can focus on improving robustness and deploying the system in mobile-based applications for real-time usage.

A. Performance Comparison with GAN-Based Augmentation

Fig. 3 illustrates the comparison of performance metrics between the model trained without GAN and the model enhanced with GAN-based data augmentation. The evaluation is carried out using standard metrics such as accuracy, precision, recall, and F1-score. It can be observed that the model integrated with GAN consistently achieves higher values across all performance metrics compared to the model without GAN. The improvement in accuracy indicates better overall classification capability. Similarly, the increase in precision reflects a reduction in false positive predictions, while the higher recall demonstrates improved detection of actual disease instances. The F1-score also shows noticeable enhancement, indicating a balanced improvement in both precision and recall.

The observed performance gain can be attributed to the increased diversity of training data generated through GAN-based augmentation, which helps the model generalize more effectively and reduces overfitting. These results validate the effectiveness of incorporating GAN in the proposed AgroBot system for plant disease detection.

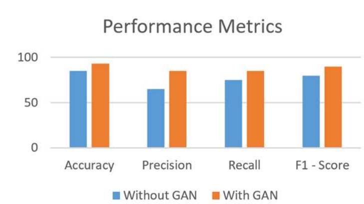

Fig 3. Performance comparison of the proposed model with and without GAN-based augmentation.

B. Comparative Summary of Existing and Proposed Systems

The comparative analysis highlights that AgroBot not only extends the technical capabilities of existing AI-based leaf disease detection systems but also introduces an ethically responsible, inclusive, and scalable framework for the digital world.

TABLE II: COMPARATIVE SUMMARY OF EXISTING SYSTEMS AND PROPOSED AGROBOT SYSTEM

Feature	Existing System	Proposed System	Advantage
Disease Detection Method	Manual inspection or basic image processing	CNN-based deep learning model	Higher accuracy and automatic feature extraction
Data Handling	Limited and imbalanced datasets	GAN-based data augmentation	Improved robustness and generalization
Government Scheme Support	Not included	Integrated scheme suggestions	Financial and recovery assistance
Accessibility	Location-dependent	Web-based access	Better decision-making
Recommendation System	Generic or expert-dependent	Disease-specific intelligent recommendations	Ensures ethical and safe AI deployment
Scalability	Limited	Highly scalable	Suitable for large-scale deployment

Table 2 shows that most existing systems primarily focus on disease identification with general treatment suggestions. In contrast, AgroBot provides a comprehensive decision-support framework that includes preventive measures, optimized pesticide recommendations, and guidance on relevant government agricultural schemes, thereby supporting farmers in both crop recovery and financial planning.

C. Model Performance Analysis

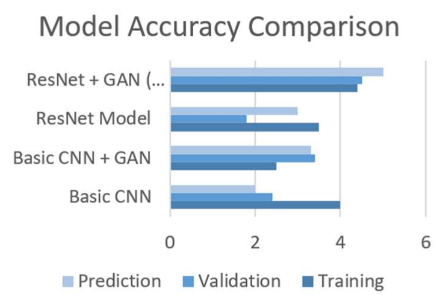

Fig 4. Comparative analysis of different models

Fig. 4 illustrates the comparative performance of different models, including Basic CNN, CNN with GAN, ResNet, and the proposed ResNet with GAN (AgroBot). The comparison is based on training, validation, and prediction metrics. It can be observed that the basic CNN model exhibits moderate performance, with relatively higher training values but lower prediction capability, indicating possible overfitting. The inclusion of GAN-based data augmentation improves the performance of the CNN model by enhancing validation and prediction outcomes.

Furthermore, the ResNet model demonstrates better generalization compared to the basic CNN due to its deep architecture and residual learning capability. However, the proposed ResNet combined with GAN achieves the best overall performance among all models. This improvement is attributed to the enhanced feature extraction of ResNet along with the increased data diversity provided by GAN-based augmentation.

The proposed approach shows higher consistency across training, validation, and prediction metrics, indicating improved robustness and reduced overfitting. These results confirm that integrating GAN with ResNet significantly enhances the accuracy and reliability of plant disease detection.

D. Training Accuracy Analysis

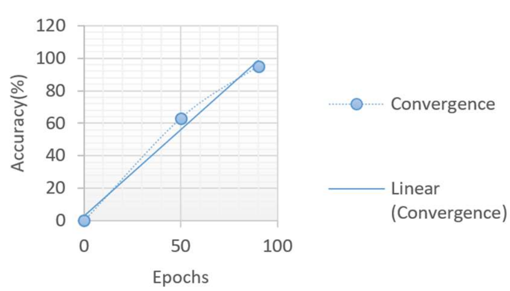

Fig 5. Accuracy convergence of the model over training epochs

Fig. 5 presents the variation of model accuracy with respect to the number of training epochs. It is observed that the accuracy increases progressively as the epochs advance, indicating effective learning of the model. Initially, the model shows low accuracy due to random weight initialization. As training continues, the model captures more relevant features from the input data, leading to a significant improvement in performance. Toward the later stages, the accuracy approaches a higher value and stabilizes, demonstrating that the model has achieved convergence. This trend confirms that the proposed approach is capable of learning complex patterns efficiently and producing reliable classification results.

E. Loss Function Analysis

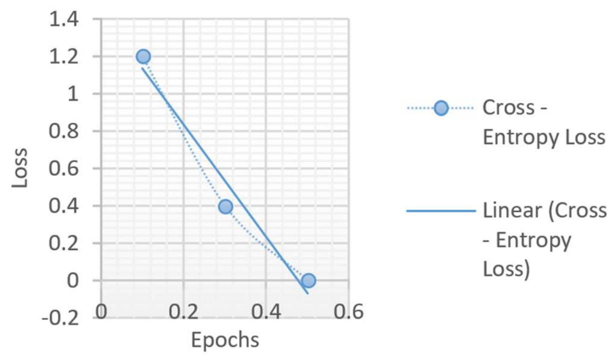

Fig 6. Loss function reduction during training epochs

Fig. 6 illustrates the reduction in loss values across training epochs using the cross-entropy loss function. The graph shows a consistent decrease in loss as the number of epochs increases, indicating that the model is effectively minimizing prediction errors. At the initial stage, the loss is relatively high due to incorrect predictions; however, it decreases significantly as the model parameters are optimized during training. In the final stages, the loss approaches a minimal value, suggesting stable convergence and improved model performance. This behaviour demonstrates the effectiveness of the training process and confirms that the model is well-optimized for the classification task.

F. Performance Metrics Evaluations

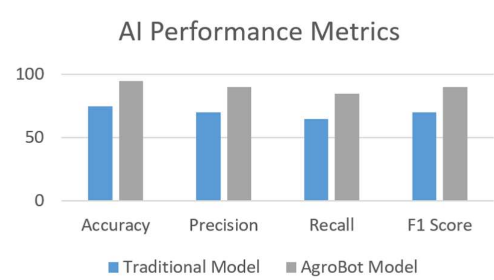

Fig 7. Performance metrics comparison of traditional and proposed models

Fig. 7 presents the comparative analysis of key performance metrics between the traditional model and the proposed AgroBot system. The evaluation is based on accuracy, precision, recall, and F1-score. It can be observed that the proposed AgroBot model consistently outperforms the traditional approach across all evaluation parameters.

The AgroBot model achieves higher accuracy, indicating its improved capability in correctly classifying plant diseases. Similarly, the precision value is significantly enhanced, demonstrating a reduction in false positive predictions. The recall metric also shows noticeable improvement, which reflects the model's effectiveness in identifying actual disease cases. Furthermore, the F1-score, which represents the harmonic mean of precision and recall, is higher for the proposed system, confirming a balanced and reliable performance.

Overall, the discussion indicate that the integration of advanced techniques in the AgroBot model leads to superior classification performance compared to the conventional model, making it more suitable for real-time plant disease detection applications.

VI. Expected Result

The proposed AgroBot system is expected to achieve high accuracy in plant disease classification by leveraging the deep feature extraction capability of the ResNet model combined with GAN-based data augmentation. The model is anticipated to outperform traditional convolutional neural network approaches in terms of accuracy, precision, recall, and F1-score. Furthermore, the system is designed to effectively identify multiple plant diseases from leaf images and provide reliable predictions.
In addition to classification, the proposed system is expected to estimate the severity level of the detected disease, thereby assisting users in understanding the extent of infection. The integration of data augmentation techniques is expected to enhance model generalization and reduce overfitting. Overall, the system is intended to deliver consistent and robust performance under varying environmental conditions, making it suitable for real-time agricultural applications.

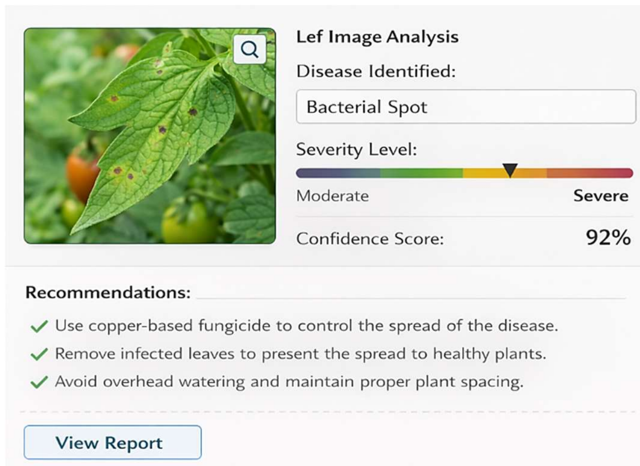

Fig 8. AgroBot Web Interface Showing Leaf Disease Detection, Severity Analysis.

Overall, the expected results indicate that AgroBot will serve as a cost-effective, user-centric, and impactful smart agriculture solution that strengthens farmer decision-making and contributes to improved crop health and food security.

VII. Equations and Calculations

This section presents the mathematical formulations used in the AgroBot system for plant disease detection, data augmentation, and performance evaluation.

Introduction to Mathematical Formulation
The proposed AgroBot system employs mathematical formulations to optimize the training process and evaluate model performance. These formulations are essential for understanding how the model learns from input data, generates predictions, and measures its effectiveness. The following equations represent the core components used in the classification and evaluation of plant leaf diseases.

Mathematical Equations and Calculations

A. Cross-Entropy Loss Function

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Explanation:
The cross-entropy loss function is used to measure the difference between the actual class labels and the predicted probabilities generated by the model. Here, $y_i$represents the true label, and $y\hat{}_i$denotes the predicted probability for class i.
A lower loss value indicates better model performance. This loss function helps the model to adjust its weights during training and improve prediction accuracy.

B. Softmax Function

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

Explanation:
The softmax function converts the raw output values (logits) of the neural network into probability values. Each output value is transformed such that the total sum of probabilities equals one. This allows the model to assign a probability score to each disease class and select the most likely class as the final prediction.

C. Accuracy

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

Explanation:
Accuracy represents the overall correctness of the model by calculating the ratio of correctly predicted instances to the total number of predictions. Here, TP (True Positive) and TN (True Negative) indicate correct predictions, while FP (False Positive) and FN (False Negative) represent incorrect predictions.

D. Precision

$$Precision = \frac{TP}{TP + FP}$$

Explanation:
Precision measures the accuracy of positive predictions made by the model. It indicates how many of the predicted disease cases are actually correct. A higher precision value means fewer false alarms.

E. Recall

$$Recall = \frac{TP}{TP + FN}$$

Explanation:
Recall evaluates the model's ability to correctly identify all actual disease cases. It reflects how well the model detects infected leaves. A higher recall value indicates fewer missed detections.

F. F1-Score

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Explanation:
The F1-score is the harmonic mean of precision and recall. It provides a balanced evaluation of the model's performance, especially when there is an imbalance between classes. A higher F1-score indicates better overall performance.

G. Disease Severity

In the proposed AgroBot system, disease severity is determined by calculating the ratio of the infected leaf area to the total leaf area. After disease classification using the trained ResNet model, image processing and segmentation techniques are applied to distinguish diseased regions from healthy tissue. The total leaf area is computed by identifying leaf pixels, while infected pixels corresponding to symptoms such as spots or discoloration are detected separately. The severity level is then expressed as the percentage of infected area relative to the total leaf area.

Severity = (Infected Area / Total Leaf Area) x100

Disease severity is calculated by determining the ratio of the infected portion of the leaf to the total leaf area. This value is expressed as a percentage and is used to categorize the infection level into mild, moderate, or severe. This step enhances the practical usability of the system by providing more detailed insights beyond simple classification.

TABLE III: DISEASE SEVERITY LEVEL CLASSIFICATION

Severity Level	Infected Leaf Area (%)	Leaf Condition Description	Recommended Action
Mild	< 25%	Minor spots or slight discoloration	Regular monitoring and preventive measures
Moderate	25% to 50%	Noticeable lesions and partial leaf damage	Application of fungicide and pruning of infected leaves
Severe	> 50%	Extensive lesions and severe leaf damage	Immediate treatment or crop removal to prevent spread

Conclusion of Mathematical Analysis

The above mathematical formulations collectively define the working mechanism of the proposed AgroBot system. The loss function ensures effective model training, while the softmax function enables accurate classification. Performance metrics such as accuracy, precision, recall, and F1-score provide a comprehensive evaluation of the model. Additionally, the disease severity calculation enhances the system by offering detailed insights into the level of infection. These formulations contribute to improving the reliability and effectiveness of the plant disease detection system.

VIII. FUTURE WORKS

Although the proposed AgroBot system demonstrates effective performance in plant disease detection and agricultural advisory services, several enhancements can be explored in future work. Future work will focus on expanding the AgroBot system to support multi-crop and multi-disease datasets under diverse real-world field conditions, including varying lighting and background environments. The model can be further enhanced using advanced architectures such as transformer-based vision models and federated learning for distributed agricultural applications. Integration with IoT sensors for real-time environmental monitoring and mobile application deployment will improve accessibility for rural farmers. Additionally, incorporating multilingual support and adaptive recommendation systems based on regional farming practices can further increase the scalability and practical impact of the proposed framework.

IX. NOVELTY

The novelty of the proposed AgroBot system presents a novel integrated framework that combines Residual Network based leaf disease classification with Generative Adversarial Network (GAN)–based data augmentation to improve robustness under imbalanced and noisy agricultural datasets. Unlike conventional plant disease detection models that focus solely on classification, AgroBot extends functionality by incorporating severity estimation, treatment recommendations, preventive measures, and guidance on relevant government agricultural schemes within a single web-based platform. Additionally, the integration of an intelligent, context-aware chatbot enables real-time farmer interaction and decision support. This unified approach transforms traditional disease detection models into a comprehensive smart advisory system for precision agriculture.

X. CONCLUSION

In this work, an intelligent plant disease detection and advisory system named AgroBot was proposed to address the challenges faced by farmers in the early identification and management of plant diseases. This paper presented AgroBot, an AI-driven leaf disease detection and intelligent advisory system designed to support smart agriculture practices. By integrating ResNet-based disease classification with GAN-based data augmentation, the proposed system enhances classification accuracy and robustness under imbalanced and noisy data conditions. Beyond detection, AgroBot provides severity analysis, treatment recommendations, preventive guidance, and access to relevant agricultural support schemes through an interactive chatbot interface. Experimental results demonstrate the effectiveness of the proposed framework, highlighting its potential as a practical and scalable solution for precision farming and farmer-centric decision support systems.

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