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Phyto Detect AI: CNN Based Automated Disease Detection in Grape Vitis Vinifera

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Abstract: Grapes are a cornerstone of the global agricultural industry, but they are often threatened by common leaf diseases like Black Rot, Esca, and Leaf Blight. These infections can devastate harvests, reduce the quality of the fruit, and cause major financial losses for growers. This paper presents an automated disease detection system using a Convolutional Neural Network (CNN) that classifies grape leaves into four categories: Healthy, Black Rot, Esca, and Leaf Blight. The model was trained on adiversedataset prepared through resizing, normalization, and augmentation techniques. After training, the model achieved a 96.8% accuracy rate and a ROC-AUC score of 0.98. The system is integrated into a user-friendly web application where farmers can upload a grape leaf image and receive an instant diagnosis, enabling early detection and sustainable vineyard management.

Keywords: Convolutional Neural Network, Deep Learning, Grape Leaf Disease Detection, Image Classification, ROC-AUC, Precision Agriculture.

INTRODUCTION

Grape cultivation is highly vulnerable to leaf diseases such as Black Rot, Esca, and Leaf Blight, which cause significant crop losses and financial damage to farmers. Traditional disease detection relies on manual inspection, which is time-consuming, labor-intensive, and often fails to identify infections at early stages. Therefore, an automated and accurate disease detection system is highly needed. This study proposes Phyto Detect AI, a CNN-based system that automatically detects and classifies grape leaf diseases through a web application, enabling farmers to receive instant diagnosis by simply uploading a leaf image, thereby supporting early intervention and sustainable vineyard management.

MATERIALS AND METHODS

The development of the Phyto Detect AI system utilized several modern technologies and tools. The model was built using Python with TensorFlow and Keras for deep learning model development. The web application was developed using the Flask framework to allow real-time image upload and disease prediction. The dataset was collected from Plant Village and other publicly available agricultural datasets, supplemented with field-captured images under varying lighting and background conditions. Version control was maintained using GitHub, and the system was deployed on a cloud server to ensure accessibility and scalability.

The development follows a structured methodology comprising six phases: Dataset Collection, Preprocessing, Model Design, Training, Evaluation, and Deployment.

1. Dataset Collection: A diverse dataset of grape leaf images was compiled containing samples of both healthy leaves and those affected by Black Rot, Esca, and Leaf Blight. Images were sourced from Plant Village and other publicly available agricultural datasets, as well as captured directly from vineyards under different environmental conditions to improve robustness.

2. Preprocessing: All images were resized to 276×276 pixels using the OpenCV library. Pixel values were normalized to a range of 0 to 1 to improve training stability. Data augmentation techniques including rotation, horizontal and vertical flipping, zooming, and brightness adjustments were applied to increase dataset variability and reduce overfitting. Disease category labels were converted to numerical values using one-hot encoding. The dataset was split into 80% for training and 20% for testing.

3. Model Architecture: The proposed system adopts a CNN-based architecture consisting of a Preprocessing Layer, Convolutional Blocks, a Flatten

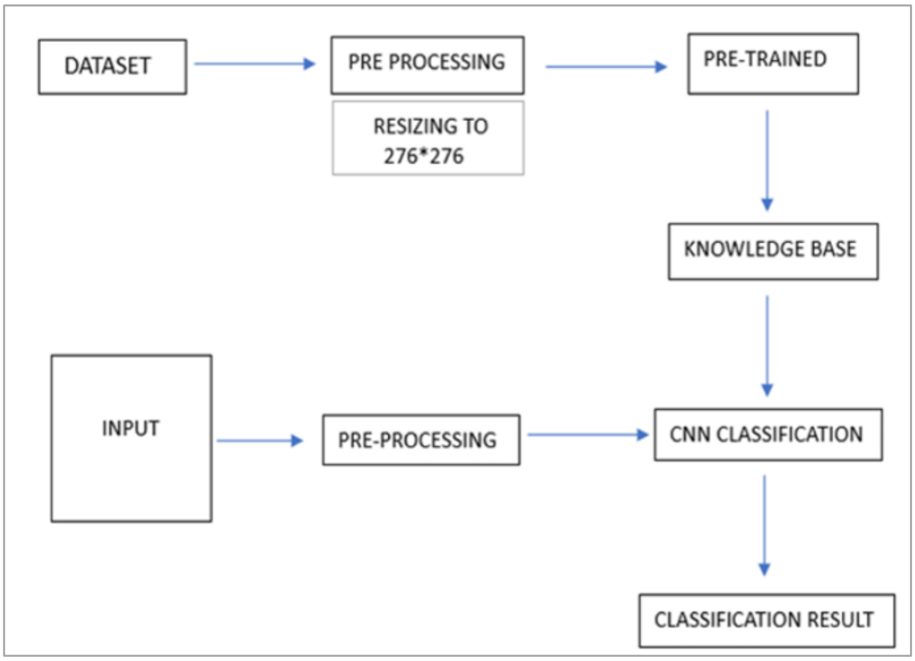
Layer, Fully-Connected Layers, and an Output Layer. The convolutional blocks use 3×3 filters with ReLU activation and Max Pooling to extract hierarchical features. The output layer uses a SoftMax activation function to generate probability distributions across four disease classes. Hyperparameter tuning was performed by testing different convolutional layer configurations, filter sizes, batch sizes, and learning rates. Transfer learning was also applied using pre-trained models such as VGG16 and ResNet50 to further improve feature extraction.

4. Volunteer Matching Algorithm: To efficiently classify grape leaf diseases, a CNN-based scoring model was implemented. Each input image is evaluated through the network layers, extracting features related to disease patterns such as dark spots, discoloration, and blight regions, ultimately producing a class probability score for each of the four categories.

5. Training: The model was trained on 2000 images using categorical cross-entropy as the loss function and the Adam optimizer over 30–50 epochs with a batch size of 32. Data augmentation was applied throughout training to improve generalization. Model performance was tracked using accuracy and validation accuracy metrics across epochs.

6. Deployment: The trained model was integrated into a Flask-based web application and deployed on a cloud server, allowing farmers to upload grape leaf images and receive real-time disease predictions. The system is accessible from multiple locations and is designed for scalability and continuous updates.

Proposed architecture for disease prediction



RESULTS

1. Functional Outcomes: The CNN-based model successfully classified grape leaves into four categories: Healthy, Black Rot, Esca, and Leaf Blight. The final test accuracy reached 98%, with precision, recall, and F1-score all at 98%. The Healthy class achieved perfect scores of 1.00 across all metrics. The ROC-AUC score reached 1.0, demonstrating the model's ability to perfectly differentiate between all disease classes. The web application was successfully deployed and allows farmers to upload images and receive instant disease predictions.

2. System Validation: The platform was validated using a test dataset comprising 20% of the total collected images. All modules including image upload, preprocessing, disease classification, and result display functioned as expected. The confusion matrix confirmed that nearly all samples were classified correctly, with only minor errors occurring between Black Rot and Esca classes. Authentication and data flow mechanisms-maintained system integrity throughout testing.

3. Social Impact: The platform empowers farmers and agricultural specialists by providing a reliable, fast, and accessible tool for early grape leaf disease detection. By reducing dependency on manual inspection and enabling early diagnosis, the system helps prevent widespread crop loss and supports sustainable farming practices. The web-based interface makes the technology accessible even in remote agricultural areas, contributing to improved livelihoods for grape farmers.

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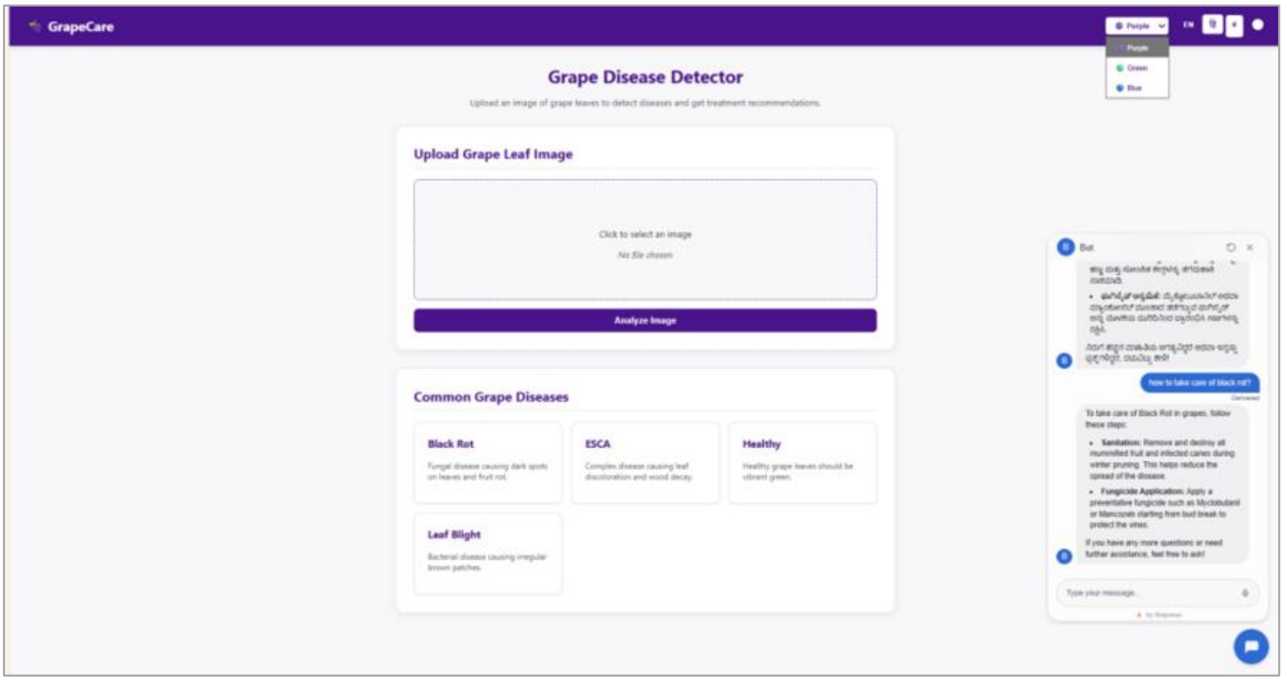
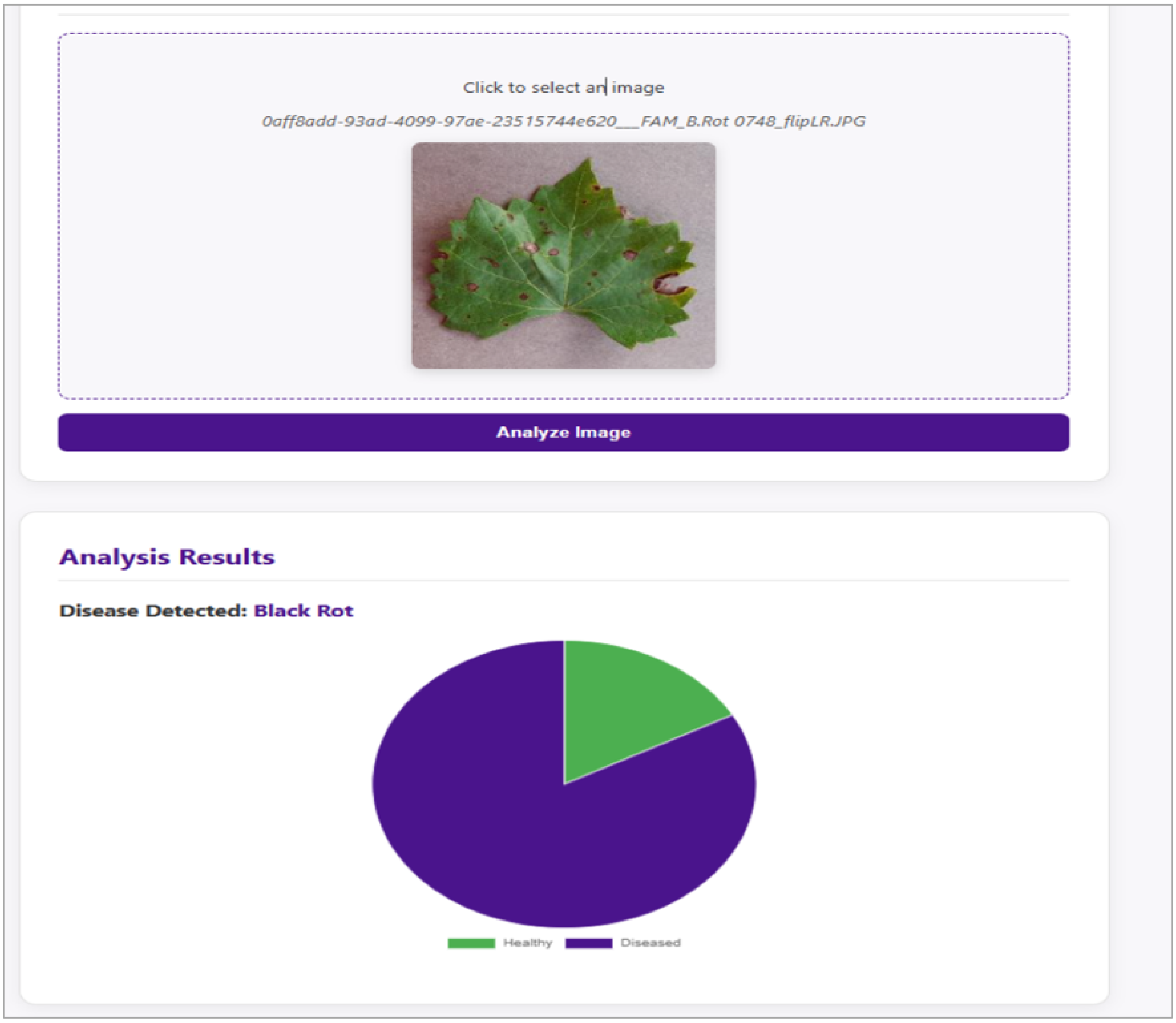
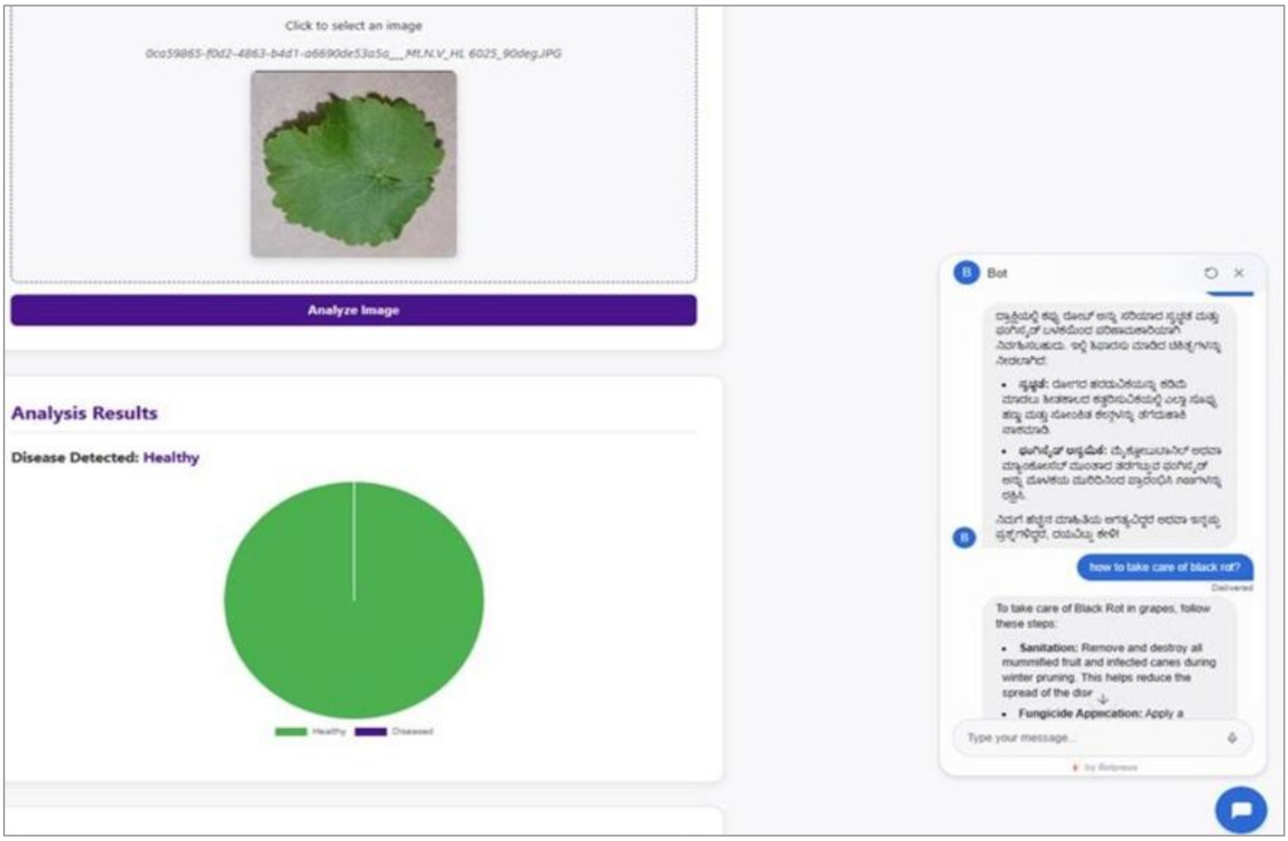

GrapeCare
Grape Disease Detector
Upload Grape Leaf Image
Click to select an image
No file chosen
Analyze Image
Common Grape Diseases
Black Rot
ESCA
Healthy
Leaf Blight


Click to select an image
0aff8add-93ad-4099-97ae-23515744e620___FAM_B.Rot 0748_flipLR.JPG
Analyze Image
Analysis Results
Disease Detected: Black Rot
Healthy
Diseased



DISCUSSION

The results demonstrate that the proposed Phyto Detect AI system effectively improves the speed and accuracy of grape leaf disease detection. The CNN-based architecture significantly outperforms traditional manual inspection methods, providing near-perfect classification results across all four disease categories. The integration of data augmentation techniques and transfer learning contributed to the model's strong generalization ability even with a limited dataset.

The implementation of a user-friendly web application ensures practical usability for farmers without requiring technical expertise. The high ROC-AUC score of 1.0 validates the model's strong discriminative ability between disease classes. The confusion matrix further confirms minimal misclassification, with only slight overlap between Black Rot and Esca categories due to their visual similarity.

Overall, the system contributes to reduced crop losses, improved disease management, and better support for precision agriculture. These outcomes highlight the potential of deep learning and AI-based platforms in transforming traditional agricultural practices.

CONCLUSION

The proposed Phyto Detect AI system effectively bridges the gap between advanced deep learning technology and practical agricultural use. It provides a centralized and accessible platform for automated grape leaf disease detection, enabling farmers to identify diseases such as Black Rot, Esca, and Leaf Blight in real time through a simple web interface. The CNN model achieved high accuracy and demonstrated strong performance across all evaluation metrics. Overall, the system demonstrates how AI and digital technology can empower farmers, enhance crop management, and contribute to sustainable and precision agriculture practice.

FUTURE WORK

1. Mobile Application (Android/iOS) – Provide on-the-go access, push notifications, and offline support for farmers in remote areas.
2. Expanded Disease Coverage – Train the model on a larger and more diverse dataset to detect a broader range of grape and multi-crop diseases.
3. IoT Integration – Integrate IoT devices and real-time image capture for continuous automated monitoring in vineyards.
4. Advanced Deep Learning Models – Implement attention mechanisms, DenseNet, or EfficientNet to further boost classification accuracy.
5. Nutrient Deficiency Detection – Expand the system to also identify nutrient deficiencies alongside disease detection.
6. 6.Multi-Language & Accessibility Support – Add regional language support and inclusive design for wider farmer adoption.
7. 7.Integration with Government & Agricultural Platforms – Increase reach and legitimacy by

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linking with government agricultural advisory systems.

8. 8.AI-Powered Fraud Detection – Prevent misuse through duplicate image submissions or false disease reporting.
9. 9.Scalability & Cloud Optimization – Enhance infrastructure to support a large number of concurrent users across regions.
10. Gamification & Farmer Engagement – Introduce reward mechanisms to encourage regular use and community reporting of disease outbreaks.

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