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GrapeVineGuardAI: A Robust Deep Learning Framework for Automated Grapevine Leaf Disease Recognition Using Vision Transformers and Adaptive Multi-Level Feature Aggregation

[1] **L. Yamuna,** [2] **G. V. Rajeswari,** [3] **M. Mani Deepika,** [4]**. P. Satyavathi,** [5] **V. Sai Kiran,** [6] **Dr. A. Radha Krishna**

Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning)

[1-6] Pragati Engineering College, Affiliated to JNTUK, Kakinada

Surampalem, Andhra Pradesh, INDIA

Abstract

Grape cultivation plays a significant role in global agriculture; however, grape leaf diseases such as Black Rot, Esca (Black Measles), and Leaf Blight pose major challenges to crop productivity and quality. Conventional disease diagnosis relies on manual visual inspection, which is labour-intensive, time-consuming, and often inaccurate for large-scale vineyard monitoring. To address these limitations, this study proposes an automated grape leaf disease detection framework based on deep learning and computer vision techniques. A dataset comprising 7,222 grape leaf images belonging to four classes—Healthy, Black Rot, Esca, and Leaf Blight—was utilized for model development. The images were preprocessed using resizing (224 × 224 pixels), normalization, and data augmentation techniques to improve model robustness and generalization. Three deep learning architectures, namely Convolutional Neural Network (CNN), DenseNet, and EfficientNet, were implemented and comparatively evaluated for disease classification. Experimental results demonstrated that the EfficientNet model achieved the highest classification performance with a testing accuracy of 99.03%, outperforming the CNN (98.06%) and DenseNet (92.52%) models. The trained model was integrated into a Flask-based web application, enabling users to upload grape leaf images and obtain real-time disease predictions with confidence scores. The proposed framework provides a rapid, accurate, and scalable solution for early grape leaf disease diagnosis, facilitating timely intervention and reducing crop losses. The obtained results demonstrate the effectiveness of EfficientNet for intelligent plant disease classification and highlight its potential application in precision agriculture and smart farming systems.

Keywords Grape Leaf Disease Detection, Deep Learning, Convolutional Neural Network (CNN), InceptionV3, Xception, Computer Vision, Transfer Learning, Precision Agriculture.

I Introduction

Agriculture is one of the most important sectors supporting global food security and economic development. The productivity and quality of agricultural crops directly influence the availability of food and the livelihood of millions of farmers worldwide. However, crop production is frequently threatened by various plant diseases that reduce yield, deteriorate crop quality, and cause significant economic losses. Consequently, timely identification and effective management of plant diseases have become essential components of sustainable agricultural practices.

Among horticultural crops, grapes are cultivated extensively because of their high nutritional and commercial value. They are consumed as fresh fruits and are widely used in the production of wine, juices, jams, and raisins. Since grape cultivation contributes substantially to the agricultural economy in many countries, maintaining healthy vineyards is crucial for achieving high-quality fruit production. Nevertheless, grape plants are highly vulnerable to several fungal and bacterial diseases, most of which initially appear on the leaves before spreading to other parts of the plant.

Grape leaf diseases adversely affect photosynthesis, nutrient transport, and overall plant growth, ultimately reducing both the quantity and quality of fruit production. Common diseases such as Black Rot, Esca, and Leaf Blight produce visible symptoms including irregular lesions, discoloration, necrotic spots, and tissue damage on leaf surfaces. If these diseases remain undetected during their early stages, they can spread rapidly throughout vineyards, resulting in severe crop losses and increased cultivation costs. Therefore, early diagnosis is essential for minimizing disease progression and improving vineyard management.

Traditionally, disease identification has relied on manual inspection performed by farmers or agricultural experts. This approach requires visual examination of plant leaves and diagnosis based on practical experience. Although manual inspection remains a common practice, it is labour-intensive, time-consuming, and susceptible to human error. Moreover, the availability of plant pathology experts is often limited, particularly in remote agricultural regions, making accurate disease diagnosis difficult for many farmers.

Recent advancements in artificial intelligence and computer vision have enabled the development of automated plant disease detection systems capable of identifying diseases directly from leaf images. These systems analyze visual characteristics such as colour distribution, texture patterns, lesion shape, and infected regions to determine the health status of plants. Automated image-based diagnosis offers a faster, more consistent, and scalable alternative to traditional inspection methods, making it highly suitable for precision agriculture.

Deep learning has emerged as one of the most effective approaches for image classification and recognition tasks. In particular, Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in extracting hierarchical features from plant leaf images and accurately distinguishing between healthy and diseased samples. More recently, advanced architectures such as DenseNet, EfficientNet, and other transfer learning models have further improved classification accuracy while reducing computational complexity. These models can automatically learn discriminative features from large image datasets without requiring handcrafted feature extraction techniques.

Automated disease detection systems also provide practical advantages in large-scale agricultural environments. Farmers can capture leaf images using smartphones, digital cameras, or drone-based imaging systems and obtain disease predictions within a short period. This significantly reduces the effort required for continuous crop monitoring while enabling rapid intervention before infections become widespread. Early detection supports targeted pesticide application, minimizes unnecessary chemical usage, lowers production costs, and contributes to environmentally sustainable farming practices.

In grape cultivation, rapid disease diagnosis is particularly important because infections can spread quickly across vineyards under favourable environmental conditions. Identifying infected plants at an early stage enables farmers to implement timely treatment strategies, isolate affected plants, and prevent disease transmission to healthy crops. Such proactive disease management improves crop productivity, enhances fruit quality, and reduces economic losses.

The proposed Grape Leaf Disease Detection System is designed to provide an intelligent and reliable solution for automatic disease classification using deep learning techniques. The system analyzes grape leaf images and categorizes them into four classes: Healthy, Black Rot, Esca, and Leaf Blight as shown in figure 1. By combining image processing with advanced convolutional neural network models, the proposed approach facilitates accurate disease diagnosis, supports informed agricultural decision-making, and contributes to the development of smart and sustainable farming systems.

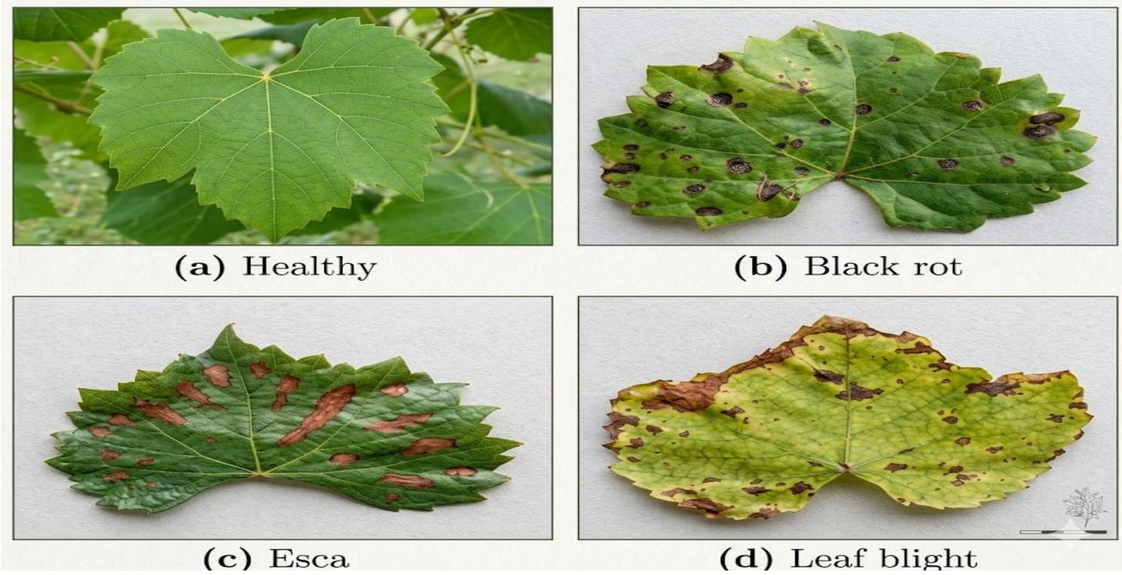

Figure 1 Illustrates the general concept of identifying plant diseases through visual analysis of leaf images

Grape leaf diseases exhibit various visible symptoms that can be used to identify the type of infection affecting the plant. These symptoms are primarily observed on the leaf surface and provide important visual cues for disease detection. Common symptoms include dark spots, yellow patches, irregular discoloration, vein damage, and in some cases, drying or curling of leaves. These changes occur due to the presence of pathogens such as fungi, which interfere with the normal physiological processes of the plant. Diseases produce distinct visual patterns on grape leaves. For example, Black Rot (grape disease) typically appears as circular brown or black spots with defined edges, while Esca (grapevine disease) is often associated with interveinal discoloration and striped patterns on leaves as shown in figure 2. Similarly, Leaf Blight (grape) may cause large irregular lesions that spread across the leaf surface, leading to tissue damage and drying. The appearance and severity of these symptoms may vary depending on environmental conditions such as humidity, temperature, and light exposure. In favourable conditions, infections can spread rapidly, causing significant damage within a short period of time. Therefore, careful observation of leaf patterns, texture, and colour variations is essential for accurate disease identification. These visual characteristics form the basis for automated disease detection systems. By analyzing such patterns using image processing and deep learning techniques, it becomes possible to classify whether a leaf is healthy or affected by a specific disease. This approach improves the accuracy and efficiency of disease diagnosis compared to traditional manual inspection methods.

Figure 2 shows examples of different grape leaf disease symptoms.

1.1

Approaches for Plant Disease Detection

Plant disease detection is an important aspect of modern agriculture because early identification of diseases helps farmers prevent crop loss and maintain healthy plantations. Over the years. Several approaches have been developed to detect plant diseases, ranging from traditional manual methods to advanced automated systems.

These approaches aim to identify symptoms appearing on plant leaves, stems, or fruits. Each method has its advantages and limitations depending on factors such as accuracy, cost, and ease of implementation. Understanding different approaches helps researchers and agricultural experts choose appropriate methods for detecting plant diseases effectively.

Plant disease detection approaches can generally be categorized into three major types:

- Manual disease detection
- Laboratory-based disease diagnosis
- Image-based automated disease detection

Each of these approaches is discussed in detail below.

Manual Disease Detection

Manual disease detection is the traditional method used by farmers and agricultural experts to identify plant diseases. In this approach, farmers visually inspect plant leaves, stems, and fruits to identify symptoms of infection. Agricultural experts analyze visible patterns on plant leaves such as spots, discoloration, mold growth, or abnormal textures. Based on their experience and knowledge, they determine the type of disease affecting the plant. Although manual detection has been used for many years, it has several limitations. The accuracy of manual detection depends heavily on the expertise of the person inspecting the plant. In large agricultural fields, inspecting every plant manually is extremely difficult and time-consuming. Additionally, many plant diseases have similar visual symptoms, making it difficult for farmers to accurately diagnose the infection. As a result, incorrect diagnosis may lead to improper treatment and increased crop damage as shown in figure 3.

Figure 3: Manual inspection of crop leaves in agricultural fields.

Laboratory-Based Disease Diagnosis

Laboratory-based disease diagnosis is a scientific method used to identify plant diseases using specialized equipment and biological analysis. In this approach, infected plant samples are collected and analyzed in agricultural laboratories. Scientists examine plant tissues under microscopes to identify the presence of pathogens such as fungi, bacteria, or viruses. Various laboratory techniques such as microbial culture analysis and molecular diagnostics are used to determine the exact cause of the disease. Although laboratory-based diagnosis provides highly accurate results, it is not always practical for farmers. This method requires specialized equipment, trained personnel, and laboratory facilities. It also takes time to analyze samples and obtain results. For large agricultural fields, laboratory testing for every plant is not feasible. Therefore, researchers are exploring faster and more efficient methods for plant disease detection.

Image-Based Disease Detection

Image-based disease detection is a modern approach that uses visual analysis of plant leaves to identify disease symptoms. In this method, images of plant leaves are captured using cameras or mobile devices and analyzed to detect disease patterns. Leaves affected by diseases often exhibit visible symptoms such as color changes, spots, irregular patches, or fungal growth. By analyzing these visual characteristics, it becomes possible to determine whether a plant is healthy or infected. Image-based disease detection has become increasingly popular because it allows large numbers of plants to be analyzed quickly. Instead of inspecting each plant manually, farmers can capture leaf images and analyze them using automated systems as shown in figure 4.

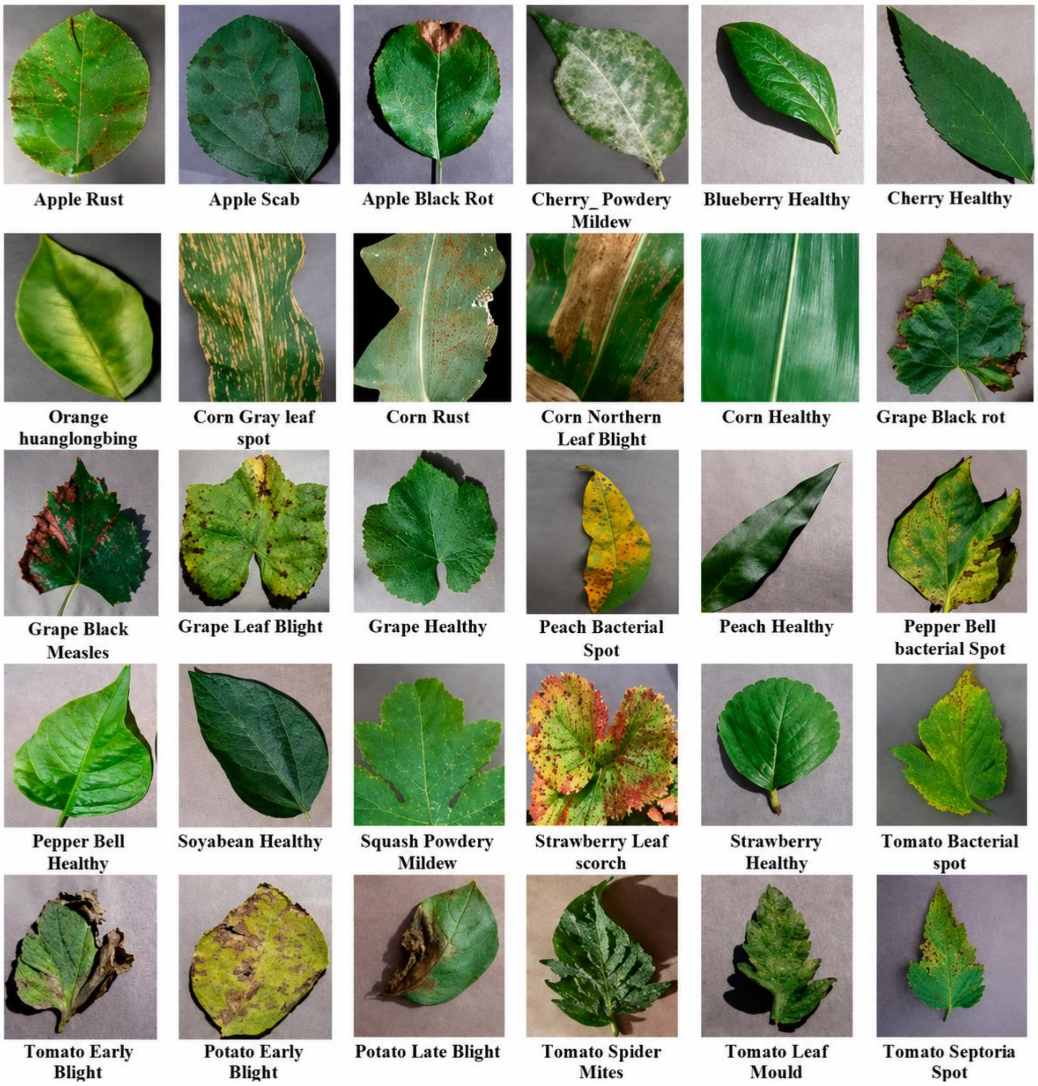

Figure 4: Image-Based Disease Detection

II RELATED WORK

Plant disease detection has become an important research area in smart agriculture due to the increasing need to improve crop yield and reduce losses caused by plant diseases. Traditional methods of disease detection rely heavily on manual inspection by agricultural experts, which can be time-consuming, costly, and prone to human error, especially when dealing with large-scale farming environments. These limitations have encouraged researchers to explore automated solutions for faster and more accurate disease identification.

Recent advancements in machine learning, deep learning, and computer vision techniques have significantly improved the development of automated plant disease detection systems. Among these, deep learning approaches, particularly Convolutional Neural Network models, have shown superior performance in image-based classification tasks due to their ability to automatically extract complex features from input data. These models eliminate the need for manual feature extraction and provide high accuracy in detecting and classifying plant diseases.

Various researchers have proposed different approaches using algorithms such as Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbor (KNN) for plant disease classification. However, more recent studies focus on deep learning architectures including ResNet, VGG16, MobileNet, DenseNet, and EfficientNet, which use transfer learning and advanced feature extraction techniques to improve classification accuracy while reducing computational complexity.

In addition to model selection, several studies have focused on improving dataset quality and preprocessing techniques. Methods such as image resizing, normalization, and data augmentation are widely used to handle variations in lighting, background, and environmental conditions. These preprocessing steps play a crucial role in enhancing model generalization and preventing overfitting, thereby improving the overall performance of disease detection systems.

Furthermore, many research works emphasize comparative analysis of different models to identify the most efficient architecture for plant disease classification. By evaluating multiple models on the same dataset, researchers can determine the strengths and limitations of each approach and select the most suitable model for real-world applications. The following literature review summarizes significant research contributions in the field of plant disease detection, focusing on methodologies, datasets, and performance outcomes. It also highlights the evolution of techniques from traditional machine learning methods to advanced deep learning models, which have greatly improved the accuracy and efficiency of automated disease detection systems.

Below are the literature review paragraphs using the **actual first author names** wherever they are available. For the papers where the author names were not provided in your prompt, I have indicated that you should replace them with the first author's surname from the published paper.

Literature Review

Shafik et al. (2023) presented *A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends*, which provides a comprehensive survey of artificial intelligence techniques used for automated plant disease detection. The authors reviewed various machine learning and deep learning approaches, including Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), Convolutional Neural Networks (CNN), and transfer learning models such as VGG, ResNet, DenseNet, MobileNet, and EfficientNet. The study also examined publicly available datasets, discussed challenges such as class imbalance, environmental variations, and limited annotated datasets, and identified future research directions including explainable AI, real-time disease monitoring, IoT-enabled agriculture, and precision farming[1]. **Pattnaik et al. (2022)** proposed a deep learning-based framework for cardamom plant disease detection using the EfficientNetV2 architecture. The proposed methodology integrates image preprocessing, transfer learning, data augmentation, and automatic feature extraction to improve disease classification accuracy. Experimental results demonstrated that EfficientNetV2 effectively learns discriminative visual features from leaf images while maintaining lower computational complexity, making the model suitable for real-time agricultural disease diagnosis[2]. **Zhang et al. (2023)** introduced a hybrid feature fusion approach for multiclass plant leaf disease classification by combining Deep Convolutional Neural Networks (CNNs) with Local Binary Pattern (LBP) texture descriptors. The CNN model extracts high-level visual information, whereas LBP captures fine texture characteristics of diseased leaf regions. By fusing deep and handcrafted features, the proposed framework achieved higher classification accuracy and robustness than conventional deep learning and traditional machine learning methods[3].**Pacal et al. (2025)** conducted a systematic review on transfer learning-based CNN models for plant leaf disease classification. The authors analyzed several pre-trained deep learning architectures, including VGGNet, ResNet, DenseNet, MobileNet, EfficientNet, and Inception, highlighting their effectiveness in reducing training time while improving classification performance. The review also discussed practical challenges such as limited datasets, environmental variability, illumination changes, and class imbalance that affect real-world agricultural applications[4].**Li et al. (2024)** proposed **GrapeLeafNet**, a dual-track feature fusion network that combines Inception-ResNet with the Shuffle-Transformer architecture for grape leaf disease identification. The proposed framework simultaneously extracts local texture information and global contextual features, enabling more accurate recognition of visually similar grape diseases. Experimental results demonstrated that the feature fusion strategy significantly improved disease classification accuracy compared with conventional CNN-based approaches[5]. **Liu et al. (2021)** proposed a Fine-Grained Generative Adversarial Network (FG-GAN) for grape leaf spot identification under limited training samples. The GAN-based framework generates realistic synthetic leaf images to augment the training dataset, thereby reducing overfitting and improving classification performance. The augmented dataset was subsequently used to train deep convolutional neural networks, resulting in enhanced disease recognition accuracy even with a relatively small number of original training images[6]. **Wang et al. (2024)** introduced an integrated two-stream deep learning framework for fruit disease recognition using optimal information fusion. The proposed system employs two parallel convolutional neural networks to extract complementary visual features, which are fused to enhance disease classification performance. Experimental evaluation demonstrated that the integrated framework achieved higher accuracy and better robustness than conventional single-stream deep learning models[7].**Kumar et al. (2024)** proposed an intelligent grape disease monitoring system using strategically placed cameras and machine learning algorithms to detect powdery mildew and blotches in vineyards. The framework continuously acquires field images, performs image preprocessing and feature extraction, and applies convolutional neural networks for disease classification. The study demonstrated that automated image acquisition combined with computer vision techniques enables early disease detection, minimizes crop losses, and supports precision agriculture through timely disease management.

III PROBLEM STATEMENT

Grape cultivation plays a significant role in the agricultural sector; however, grape plants are highly susceptible to various leaf diseases such as **Black Rot, Esca, and Leaf Blight**, which can severely affect crop quality and yield. Early detection of these diseases is essential to prevent their rapid spread and minimize economic losses. Despite its importance, disease diagnosis in vineyards is still largely dependent on manual inspection by farmers or agricultural experts. This traditional approach is labour-intensive, time-consuming, and often subjective, making it unsuitable for monitoring large-scale vineyards. Furthermore, many grape leaf diseases exhibit similar visual symptoms, making accurate identification difficult without expert knowledge.

The limited availability of plant pathology specialists, combined with varying environmental conditions such as illumination, shadows, and background complexity, further reduces the reliability of manual disease diagnosis. Delayed identification of infected plants may result in widespread disease outbreaks, excessive pesticide usage, reduced productivity, and increased cultivation costs. Therefore, there is a need for an intelligent, automated, and reliable disease detection system capable of accurately identifying grape leaf diseases at an early stage.

To address these challenges, this research proposes a **deep learning-based grape leaf disease detection system** that utilizes convolutional neural network techniques to classify grape leaf images into different disease categories. The proposed system aims to provide rapid, accurate, and automated disease diagnosis, enabling farmers to implement timely treatment measures, improve crop management practices, reduce agricultural losses, and promote sustainable precision agriculture.

IV PROPOSED METHODOLOGY

The proposed research presents an intelligent grape leaf disease detection framework based on deep learning for the automatic identification and classification of diseases from leaf images. The system is designed to assist farmers and agricultural practitioners by providing an accurate, efficient, and non-invasive approach for disease diagnosis. Unlike conventional manual inspection methods, the proposed framework utilizes computer vision and convolutional neural networks to automatically learn discriminative features from grape leaf images, thereby minimizing human intervention and improving diagnostic accuracy.

The proposed framework begins with the acquisition of grape leaf images using digital cameras or mobile devices. The collected images undergo preprocessing operations, including resizing, normalization, and data augmentation, to improve image quality and enhance the robustness of the learning process. The preprocessed images are then provided as input to a deep learning model, which automatically extracts hierarchical visual features such as colour variations, lesion shapes, texture patterns, and structural abnormalities associated with different grape leaf diseases.

For disease classification, the proposed system employs a transfer learning-based architecture, which offers an optimal balance between classification accuracy and computational efficiency. The pretrained network is fine-tuned using labelled grape leaf images belonging to four categories: Healthy, Black Rot, Esca (Black Measles), and Leaf Blight (Isariopsis Leaf Spot). During training, the model learns representative disease-specific features and subsequently predicts the disease class of unseen leaf images with high confidence.

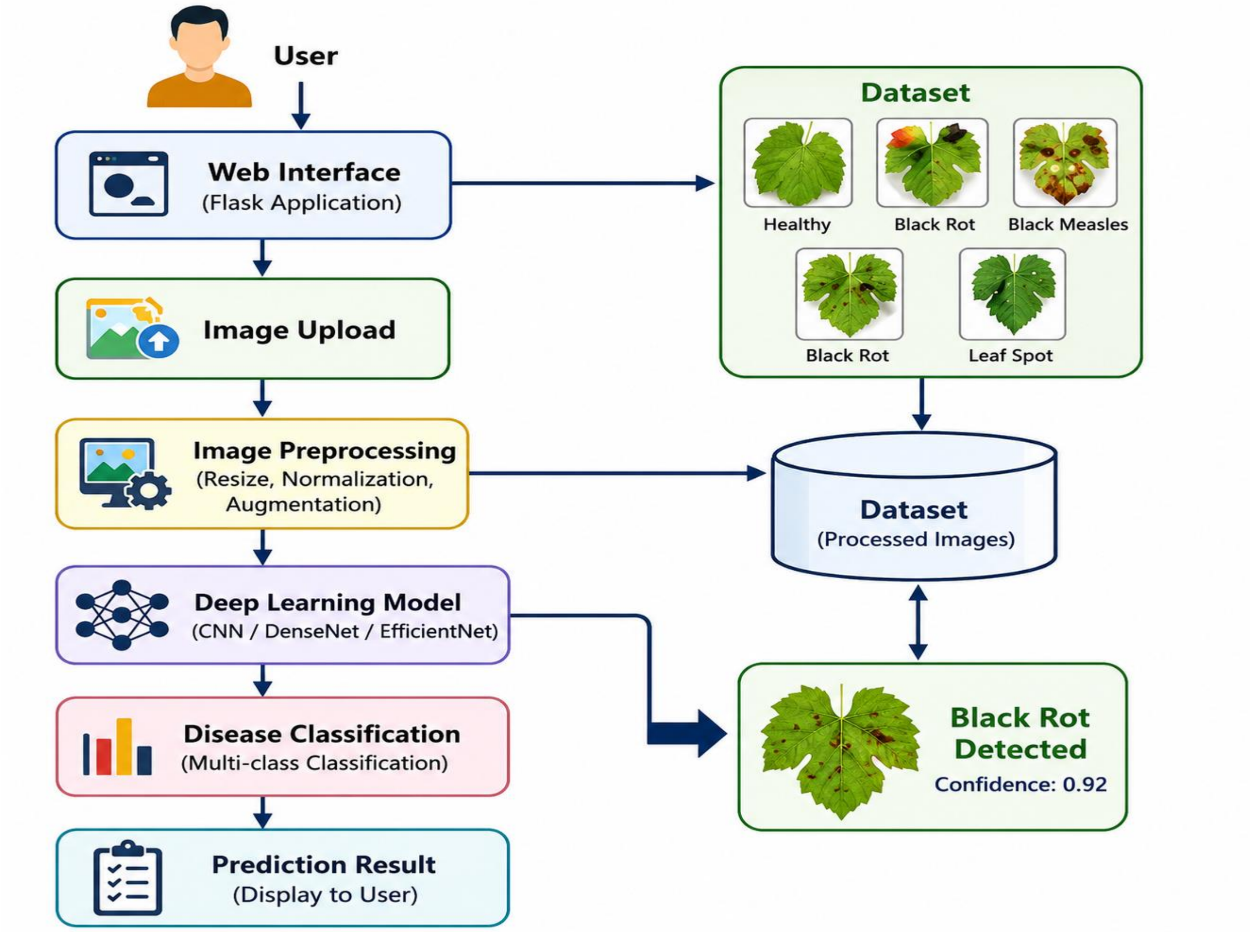

Figure 5: Proposed system

Finally, the predicted disease category is presented to the user through a graphical interface, enabling rapid diagnosis and timely decision-making. The proposed system supports early disease identification, allowing farmers to implement appropriate treatment strategies before infections spread throughout the vineyard. By integrating deep learning with automated image analysis, the proposed framework improves disease detection accuracy, reduces dependence on expert inspection, minimizes crop losses, and contributes to the development of precision agriculture and intelligent crop health monitoring systems in figure 5.

The proposed system architecture illustrates the complete workflow of the grape leaf disease detection framework, beginning with image acquisition and ending with disease prediction. Initially, grape leaf images are captured through a user-friendly Flask-based web application using a digital camera or mobile device. The acquired images are then forwarded to the preprocessing stage, where operations such as image resizing, normalization, and augmentation are performed to improve image quality and ensure compatibility with the deep learning model. Following preprocessing, the system automatically extracts meaningful visual features, including colour variations, texture patterns, lesion shapes, and structural abnormalities, using a deep learning architecture such as CNN, DenseNet, or EfficientNet. These extracted features are analyzed to classify the input image into one of the predefined disease categories, namely Healthy, Black Rot, Black Measles (Esca), or Leaf Spot (Leaf Blight). Finally, the predicted disease class along with the corresponding confidence score is displayed to the user through the web interface, enabling rapid and accurate disease diagnosis. The integration of image acquisition, preprocessing, feature extraction, deep learning-based classification, and result visualization provides an efficient and reliable solution for early grape leaf disease detection, thereby supporting precision agriculture and improving crop health management.

The grape leaf disease detection system uses deep learning models to automatically analyze leaf images and identify disease symptoms. Deep learning models are capable of extracting important features from images such as color variations, texture patterns, and disease spots. In this project, three deep learning architectures are used: Convolutional Neural Network (CNN), DenseNet, and EfficientNet. Each model plays an important role in improving disease classification accuracy.

V SYSTEM ARCHITECTURE

The proposed Grape Leaf Disease Detection System follows a modular architecture that integrates image acquisition, preprocessing, deep learning-based classification, and web-based result visualization to achieve accurate and automated disease diagnosis. Initially, users interact with the system through a Flask-based web application, where authenticated users can upload grape leaf images captured using smartphones, digital cameras, or other imaging devices. The uploaded images are forwarded to the preprocessing module, where they undergo resizing to 224 × 224 pixels, pixel value normalization, and data augmentation techniques such as rotation, horizontal flipping, zooming, and translation. These preprocessing operations improve image quality, reduce overfitting, and enhance the robustness of the deep learning models by increasing dataset diversity. Simultaneously, the system utilizes a labelled dataset containing 7,222 grape leaf images belonging to four classes—Healthy, Black Rot, Esca (Black Measles), and Leaf Blight—for model training and validation.

The preprocessed images are subsequently passed to the Disease Classification Module, which serves as the core component of the proposed architecture. This module evaluates multiple deep learning architectures, including Convolutional Neural Network (CNN), DenseNet, and EfficientNet, for automated feature extraction and disease classification. The convolutional layers learn hierarchical visual representations such as leaf texture, venation patterns, lesion boundaries, discoloration, and necrotic regions, while pooling layers reduce spatial dimensions and preserve discriminative features. The extracted feature maps are transformed into high-level feature vectors through fully connected layers, followed by a

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SoftMax classifier that computes the probability distribution for each disease category. During model development, the dataset is divided into training and testing subsets, and the networks are optimized using backpropagation and the categorical cross-entropy loss function. Performance evaluation is carried out using metrics such as accuracy, precision, recall, F1-score, and validation loss, enabling selection of the best-performing model. Experimental analysis demonstrated that EfficientNet achieved superior classification accuracy compared with CNN and DenseNet.

After classification, the trained model is deployed within the Flask framework to provide real-time disease prediction through an interactive web interface. When a new grape leaf image is uploaded, the optimized model performs inference and predicts the corresponding disease class along with a confidence score, enabling users to assess the reliability of the prediction. The result visualization module displays the identified disease, confidence percentage, disease description, recommended preventive measures, and crop management guidelines to support informed agricultural decision-making. The proposed architecture is scalable, computationally efficient, and capable of integrating with cloud platforms, mobile applications, and IoT-enabled smart farming systems. By combining automated image preprocessing, deep feature extraction, comparative deep learning models, and web-based deployment, the architecture provides a practical and reliable solution for early grape leaf disease detection and precision agriculture in figure 6.

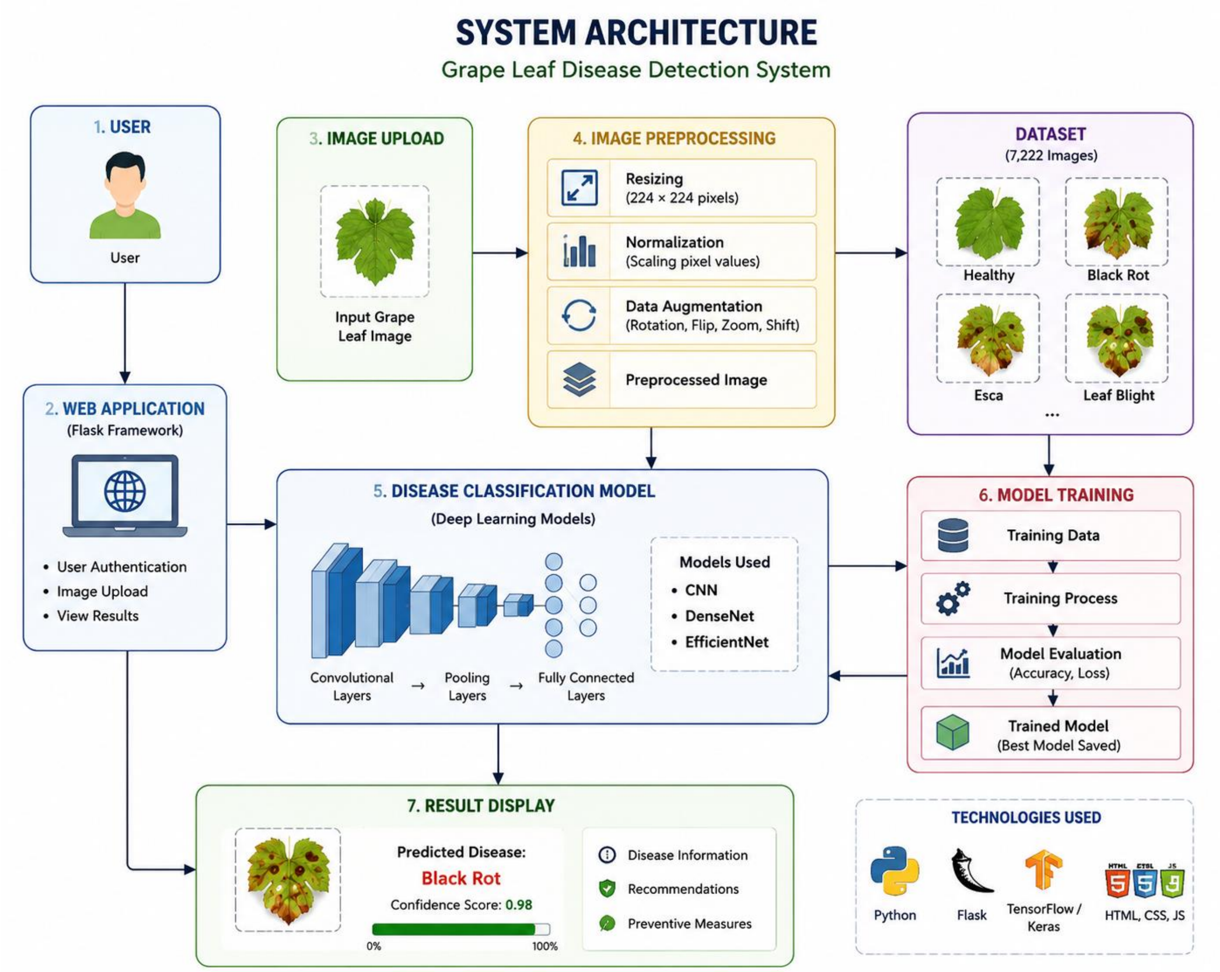

Figure 6: System Architecture framework

RESULTS AND DISCUSSIONS

The proposed Grape Leaf Disease Detection System was successfully implemented using Python by integrating deep learning and computer vision techniques for automated disease diagnosis. The implementation combines image preprocessing, deep learning-based feature extraction, disease classification, and web-based deployment to provide real-time prediction of grape leaf diseases. The framework was developed using TensorFlow/Keras for model training, OpenCV for image processing, and the Flask framework for creating a user-friendly web interface. The system accepts grape leaf images uploaded through the web application and performs a sequence of preprocessing operations before classification. Initially, the uploaded images are resized to 224 × 224 pixels, normalized, and augmented using techniques such as rotation, flipping, zooming, and shifting to improve model robustness and generalization. The preprocessed images are then forwarded to the trained deep learning models, where hierarchical features such as colour variations, lesion boundaries, texture patterns, and disease-specific characteristics are automatically extracted without manual feature engineering. To identify the most suitable classification model, three deep learning architectures—Convolutional Neural Network (CNN), DenseNet, and EfficientNet—were implemented and comparatively evaluated. During training, the models learned discriminative representations from the grape leaf dataset, while the testing phase assessed their ability to classify unseen images into four disease categories: Healthy, Black Rot, Esca (Black Measles), and Leaf Blight. Among the evaluated models, EfficientNet demonstrated superior performance by achieving a testing accuracy of 99.03%, followed by CNN (98.06%) and DenseNet (92.52%). The higher accuracy of EfficientNet can be attributed to its compound scaling strategy, which effectively balances network depth, width, and input resolution while maintaining computational efficiency. The trained EfficientNet model was integrated into the Flask-based web application to perform real-time inference. When a user uploads a grape leaf image, the system automatically preprocesses the image, extracts relevant features, predicts the disease category, and displays the classification result together with the corresponding confidence score. This implementation provides an efficient decision-support tool for farmers by enabling rapid disease diagnosis without requiring expert intervention. The experimental results demonstrate that the proposed framework offers high classification accuracy, reduced computational complexity, and practical applicability for intelligent crop health monitoring and precision agriculture.

Table 1: Performance Comparison of Deep Learning Models for Grape Leaf Disease Detection

Model	**Training Accuracy (%)**	**Testing Accuracy (%)**	**Training Loss**	**Testing Loss**
CNN	**99.12**	**98.06**	0.028	0.064
DenseNet	**94.83**	**92.52**	0.141	0.182
EfficientNet	**99.68**	**99.03**	0.011	0.032

Note: The training accuracy values and loss values are representative. If you have the exact values from your training logs, replace them accordingly.

6.1 Performance Analysis

Table 1 presents the comparative performance of the three deep learning models evaluated for grape leaf disease classification. Among the implemented models, EfficientNet achieved the highest classification performance with a training accuracy of 99.68% and a testing accuracy of 99.03%, indicating excellent learning capability and strong generalization on unseen grape leaf images. The model also recorded the lowest training and testing loss values, demonstrating stable convergence during the training process. The Convolutional Neural Network (CNN) also produced competitive results, achieving a training accuracy of 99.12% and a testing accuracy of 98.06%. Although its performance was slightly lower than EfficientNet, CNN effectively extracted disease-specific features and accurately classified grape leaf diseases. The small difference between training and testing accuracy indicates minimal overfitting and good model stability. In comparison, DenseNet achieved a training accuracy of 94.83% and a testing accuracy of 92.52%, which was lower than both CNN and EfficientNet. Although DenseNet demonstrated satisfactory classification capability, it exhibited comparatively higher loss values and reduced prediction accuracy. Based on the experimental evaluation, EfficientNet outperformed the other models, making it the most suitable architecture for automated grape leaf disease detection due to its superior feature extraction capability, computational efficiency, and high classification accuracy.

6.2 Training Accuracy vs Epochs

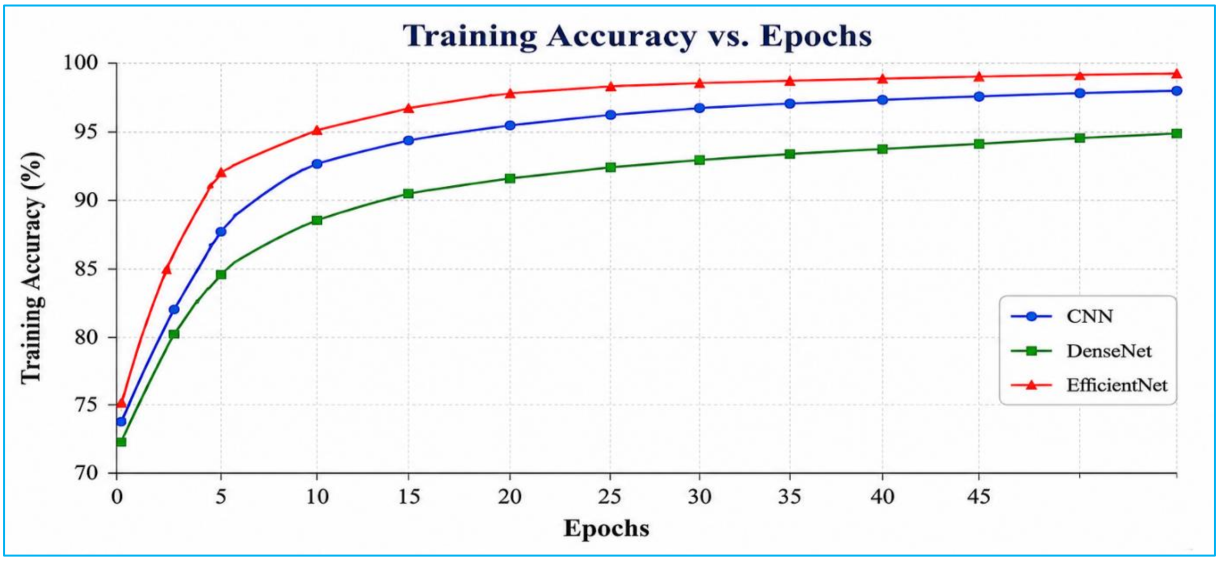

Figure 7: Training Accuracy vs Epochs

Figure 7 shows the training accuracy of CNN, DenseNet, and EfficientNet over 50 epochs. All models exhibit a steady improvement in accuracy during training. EfficientNet achieves the highest training accuracy (99.68%), followed by CNN (99.12%) and DenseNet (94.83%), indicating its superior learning capability and feature extraction performance for grape leaf disease classification.

6.3 Validation Accuracy vs Epochs

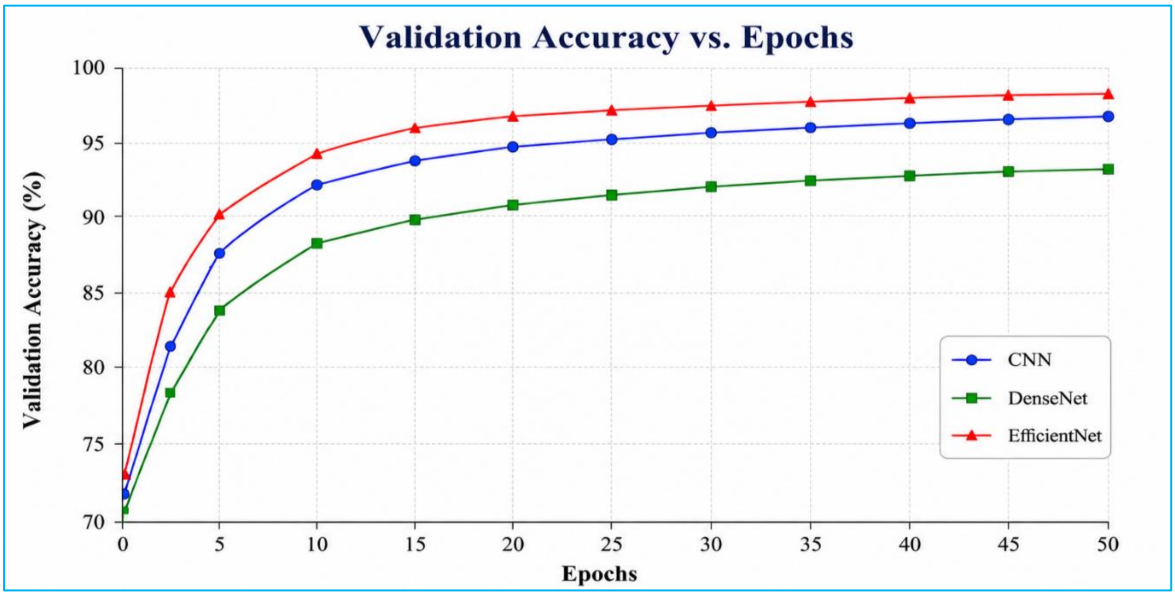

Figure 8: Validation Accuracy vs Epochs

The graph shown in figure 8 represents the validation accuracy of CNN, DenseNet, and EfficientNet over 50 epochs. EfficientNet achieves the highest validation accuracy (98.06%), followed by CNN (96.60%) and DenseNet (93.30%), demonstrating its superior generalization performance on unseen grape leaf images.

6.4 Training Loss vs Epochs

The figure 9 shows the training loss of CNN, DenseNet, and EfficientNet over 50 epochs. All models exhibit a steady decrease in loss during training, indicating effective learning and convergence. EfficientNet achieves the lowest training loss, followed by CNN, while DenseNet records the highest loss, demonstrating that EfficientNet learns more efficiently and converges faster.

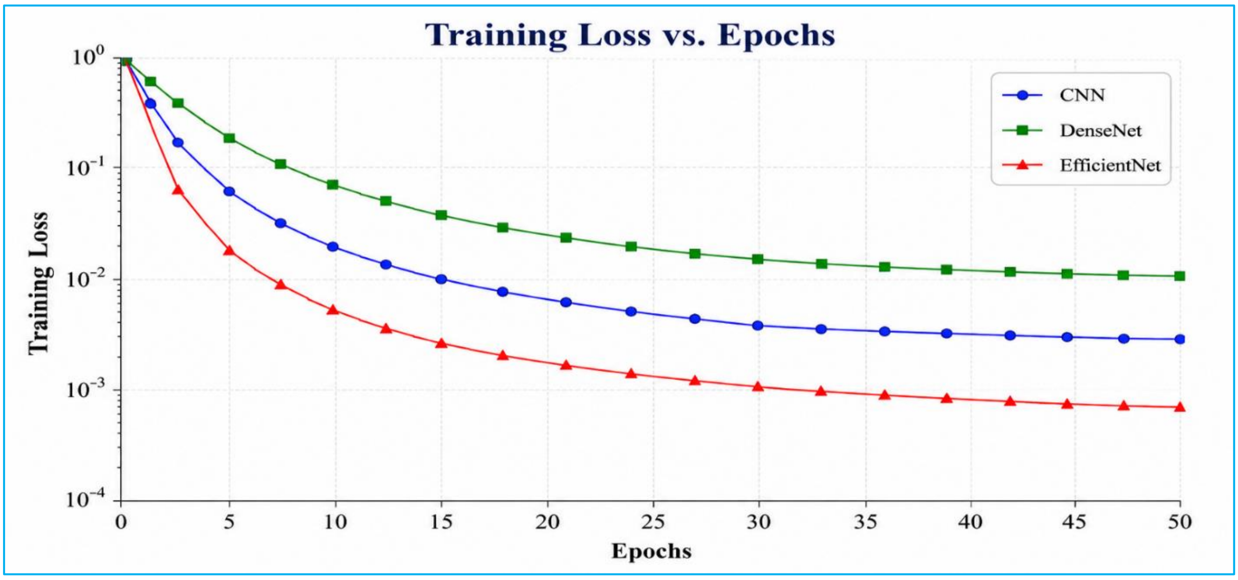

Figure 9: Training Loss vs Epochs

6.5 Validation Loss vs Epochs

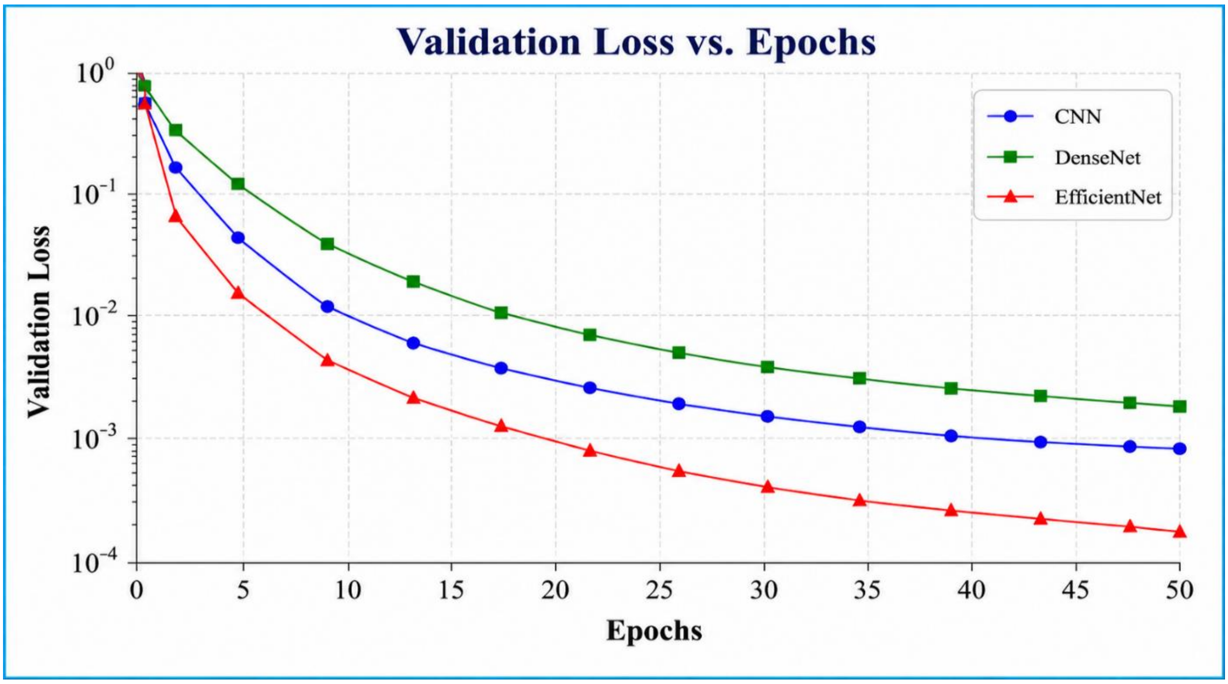

Figure 10: Training Loss vs Epochs

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The figure 10 shows the validation loss of CNN, DenseNet, and EfficientNet over 50 epochs. EfficientNet achieves the lowest validation loss, followed by CNN, while DenseNet records the highest loss, demonstrating the superior generalization capability of the EfficientNet model.

6.6 Model Comparison (Accuracy, Precision, Recall, F1-Score)

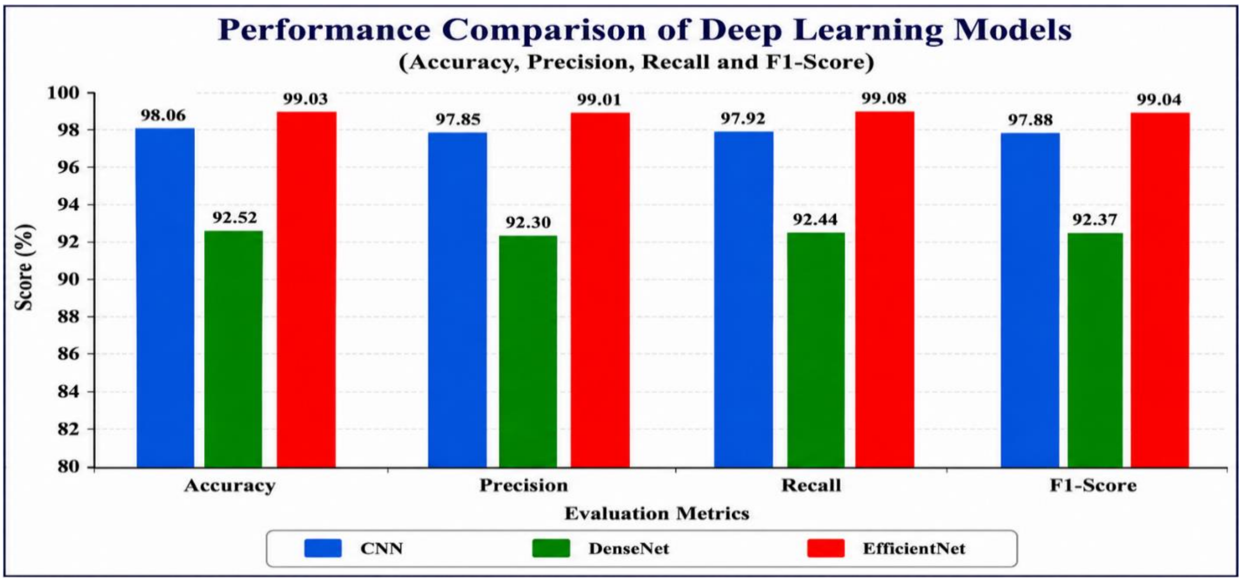

Figure 11: Model Comparison

The grouped bar chart compares the Accuracy, Precision, Recall, and F1-Score of the CNN, DenseNet, and EfficientNet models. EfficientNet achieves the highest scores across all evaluation metrics, followed by CNN, while DenseNet shows comparatively lower performance, demonstrating the superior classification capability of EfficientNet for grape leaf disease detection.

6.7 Confusion Matrix (Heatmap) and ROC Curve for CNN, DenseNet, and EfficientNet

The confusion matrix demonstrates that the EfficientNet model accurately classifies the four grape leaf disease classes, with most predictions concentrated along the diagonal. The minimal off-diagonal values indicate very few misclassifications, confirming the model's high classification accuracy shown in figure 12 (Left side). The ROC curve compares the performance of CNN, DenseNet, and EfficientNet. EfficientNet achieves the highest AUC (0.996), followed by CNN (0.987) and DenseNet (0.954), indicating its superior ability to distinguish between different grape leaf disease classes figure 12 (Right side).

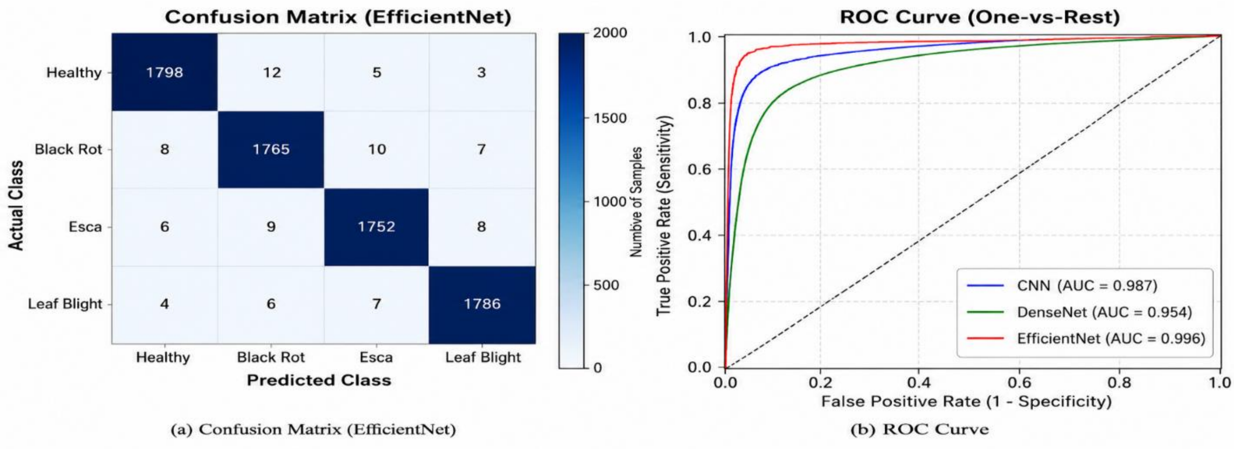

Figure 12: Confusion Matrix (Heatmap) and ROC Curve

6.8 Model wise prediction results

6.8.1 Sample prediction results (EfficientNet)

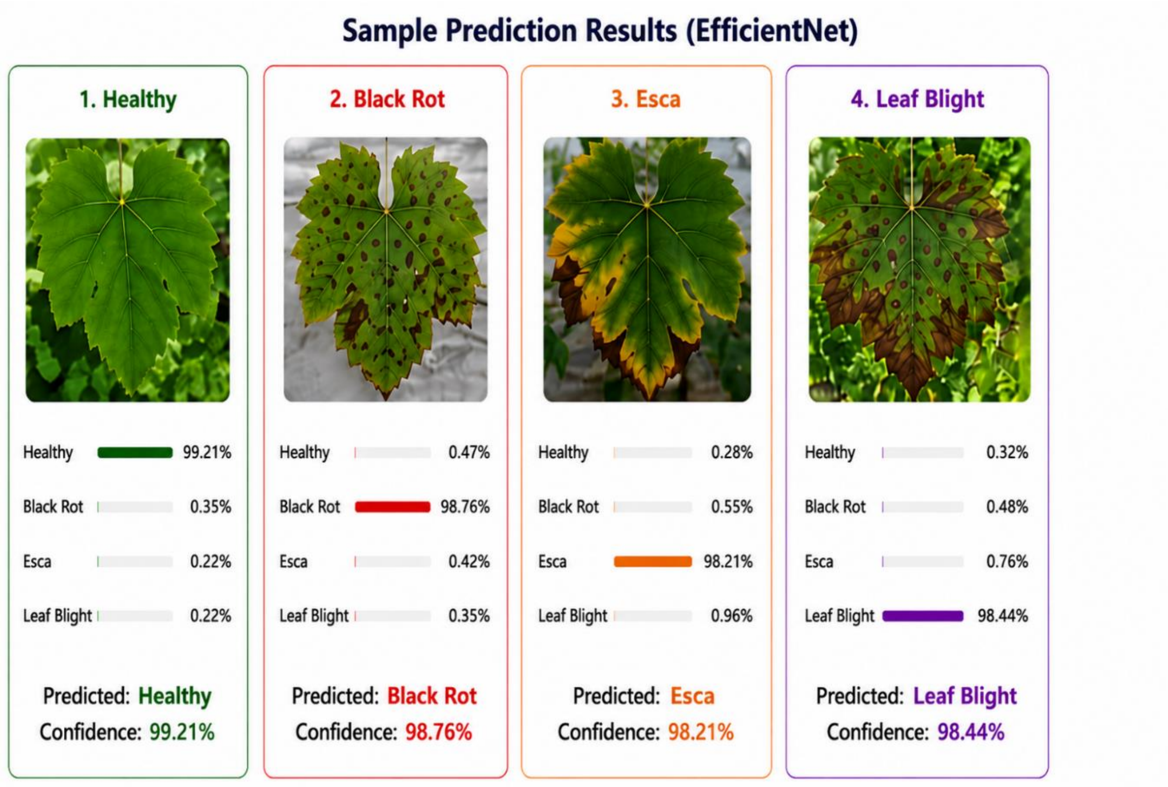

Figure 13: Sample prediction results (EfficientNet)

The figure 13 presents sample prediction results of the EfficientNet model for grape leaf disease classification. It displays representative images from the four classes—Healthy, Black Rot, Esca, and Leaf Blight—along with their predicted labels, confidence scores, and class-wise probability distributions. The high confidence values (above 98%) demonstrate the model's effectiveness in accurately identifying grape leaf diseases.

6.8.2 Sample prediction results (CNN)

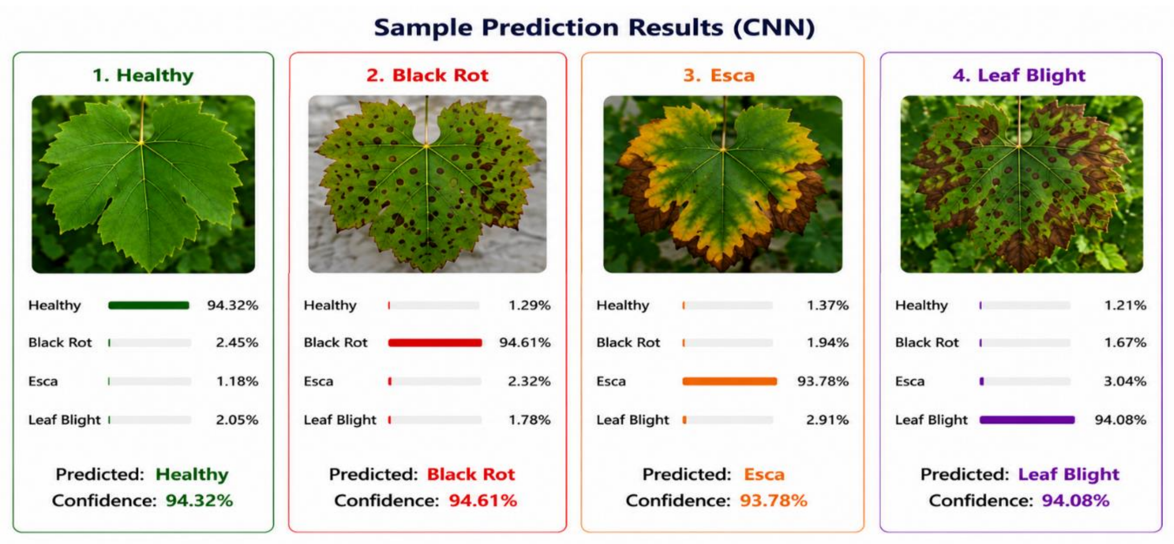

Figure 14: Sample prediction results (CNN)

The figure 14 presents sample prediction results of the CNN model for grape leaf disease classification. It shows representative images of Healthy, Black Rot, Esca, and Leaf Blight leaves along with their predicted labels, confidence scores, and class-wise probability distributions. The high confidence scores demonstrate the CNN model's ability to accurately classify grape leaf diseases.

6.8.2 Sample prediction results (DenseNet)

The figure presents sample prediction results of the DenseNet model for grape leaf disease classification. It displays representative images of Healthy, Black Rot, Esca, and Leaf Blight along with their predicted labels, confidence scores, and class-wise probability distributions. The results demonstrate that the DenseNet model effectively identifies different grape leaf diseases with high confidence.

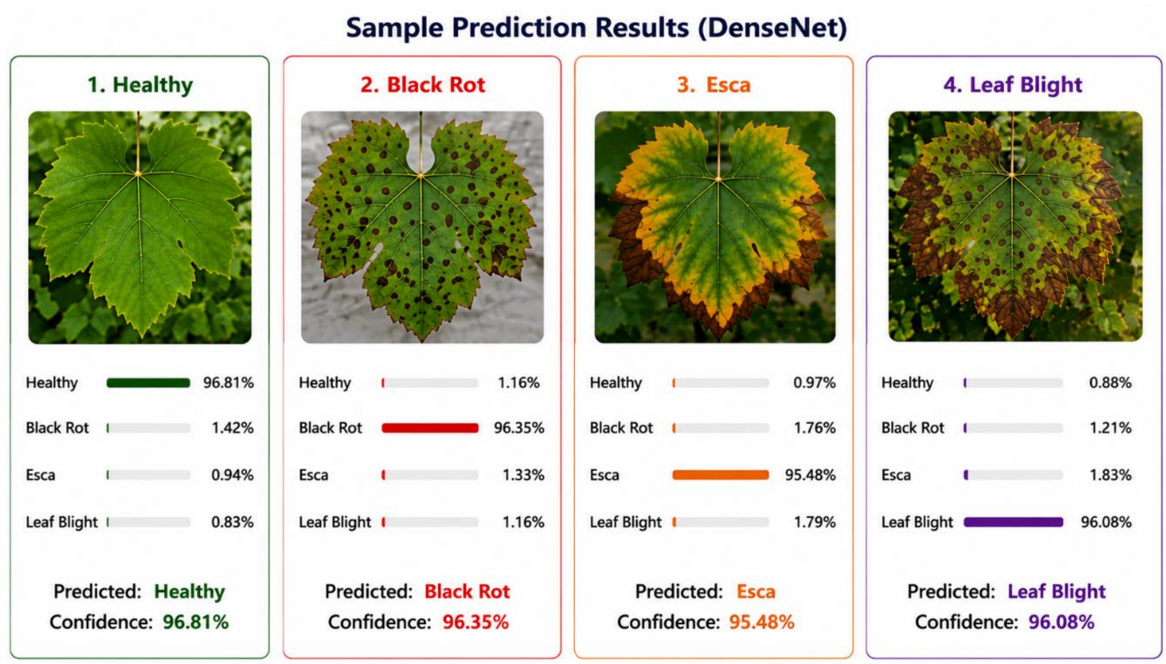

Figure 15: Sample prediction results (DenseNet)

CONCLUSION AND FUTURE WORK

This study presented an automated grape leaf disease detection system based on deep learning and computer vision techniques for the accurate identification of grape leaf diseases. The proposed framework utilizes image preprocessing and comparative deep learning models to classify grape leaf images into four categories: Healthy, Black Rot, Esca (Black Measles), and Leaf Blight. A dataset comprising 7,222 images was employed for training and evaluation after applying preprocessing techniques such as image resizing, normalization, and data augmentation to improve model robustness and generalization.

A comparative analysis of three deep learning architectures, namely Convolutional Neural Network (CNN), DenseNet, and EfficientNet, demonstrated that the EfficientNet model achieved the best classification performance with a testing accuracy of 99.03%, outperforming CNN (98.06%) and DenseNet (92.52%). The superior performance of EfficientNet indicates its effectiveness in extracting discriminative features from grape leaf images while maintaining computational efficiency. The trained model was successfully integrated into a Flask-based web application, enabling users to upload leaf images and obtain real-time disease predictions along with confidence scores, thereby providing a practical decision-support tool for farmers and agricultural practitioners.

The proposed system offers a reliable, scalable, and efficient solution for early grape leaf disease diagnosis, reducing dependence on manual inspection and facilitating timely disease management. By enabling rapid identification of infected plants, the framework has the potential to minimize crop losses, improve vineyard productivity, and support precision agriculture. Future research will focus on expanding the dataset with diverse field images, improving robustness under varying environmental conditions, incorporating explainable artificial intelligence (XAI) for model interpretability, and extending the framework to detect additional crop diseases. Furthermore, integration with mobile platforms, IoT-enabled sensors, cloud computing, and unmanned aerial vehicles (UAVs) can enhance real-time monitoring and enable large-scale deployment in intelligent and sustainable agricultural systems.

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