IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

Grapes Disease Detection Using Deep Learning

Roshan Arote, Chirag Baphana, Shubham Gunjal, Shubham Gavhane, Prof. Dr. Prajakta Shirke
Department of Computer Science & Engineering with Specialization AI&ML
Sandip University, Nashik, India

Abstract: *Grapevine diseases pose a significant threat to agricultural productivity, leading to substantial economic losses. This research presents a deep learning-based approach for detecting diseases in grape crops using convolutional neural networks (CNNs). The model is developed using TensorFlow and Keras, leveraging a labeled dataset of grape leaf images to classify healthy and diseased samples. Data preprocessing techniques, including image augmentation and normalization, enhance model performance. Visualization tools such as Matplotlib provide insights into data distribution and training progress. The system is implemented in Google Colab, integrating cloud-based storage for efficient data handling. Experimental results demonstrate high accuracy in disease classification, highlighting the potential of deep learning for precision agriculture. This automated disease detection system enables early intervention, aiding farmers in reducing crop losses and improving vineyard management. Future advancements may incorporate real-time monitoring and enhanced model generalization for broader agricultural applications..*

Keywords: Grape Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), TensorFlow, Keras, Image Classification, Precision Agriculture, Plant Health Monitoring, Automated Disease Detection, Computer Vision

I. INTRODUCTION

Agriculture plays a vital role in global food security, with vineyards being an important part of the horticultural industry. However, grape crops are highly susceptible to various fungal, bacterial, and viral diseases that can significantly reduce yield and quality. Traditional disease detection methods rely on manual inspection, which is time-consuming, labor-intensive, and prone to human error. The need for an automated, efficient, and accurate disease detection system has driven the adoption of deep learning techniques in precision agriculture.

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in image classification tasks, making it an ideal solution for plant disease detection. By leveraging TensorFlow and Keras, this research develops a CNN-based model for identifying diseases in grape leaves using image datasets. The proposed system is trained on a labeled dataset containing healthy and diseased grape leaf images, allowing it to classify plant health with high accuracy.

The research focuses on several key aspects, including data preprocessing, model architecture, and performance evaluation. Data preprocessing techniques, such as image augmentation and normalization, enhance model generalization, while visualization tools like Matplotlib help in analyzing training progress. The model is implemented in Google Colab, ensuring seamless data handling and scalability.

This study aims to contribute to the advancement of precision farming by providing an automated disease detection system that enables early intervention, reduces crop losses, and supports sustainable agricultural practices. The results demonstrate the effectiveness of deep learning in plant disease identification, paving the way for future enhancements such as real-time monitoring and integration with Internet of Things (IoT)-based agricultural systems.

II. LITERATURE REVIEW

Plant disease detection has been an area of significant research interest due to its impact on agricultural productivity and food security. Traditional disease identification methods involve manual observation by farmers or experts, which is time-consuming, prone to errors, and often ineffective in large-scale farming. To overcome these challenges, recent

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

advancements in artificial intelligence (AI) and deep learning have paved the way for automated and highly accurate plant disease detection systems.

Traditional Methods for Plant Disease Detection.

Earlier approaches to plant disease detection relied on manual scouting and laboratory testing. Farmers visually inspected crops for disease symptoms, while laboratory methods such as polymerase chain reaction (PCR) and enzyme-linked immunosorbent assay (ELISA) were used for accurate pathogen identification. However, these methods have limitations, including high costs, the need for expert intervention, and delays in disease diagnosis, leading to potential crop losses.

Machine Learning Approaches in Disease Detection.

With the rise of AI, machine learning (ML) techniques have been applied to plant disease classification. Researchers have used supervised learning algorithms such as Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (KNN) to classify diseased and healthy plant leaves. While these methods have shown promising results, they rely heavily on handcrafted feature extraction, making them less effective in complex image classification tasks.

Deep Learning for Plant Disease Classification.

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized plant disease detection by automating feature extraction and improving classification accuracy. Several studies have demonstrated the effectiveness of CNNs in agricultural applications:

- **Mohanty et al. (2016)** applied CNNs to plant leaf images and achieved over 99% accuracy in classifying 14 crop diseases using the PlantVillage dataset.
- **Ferentinos (2018)** developed a deep learning-based model for detecting multiple plant diseases with an accuracy exceeding 95%, showcasing the potential of CNNs for real-world agricultural applications.
- **Sandler et al. (2019)** implemented a MobileNet-based deep learning model for plant disease detection, optimizing computational efficiency for real-time use in mobile devices.

Grape Disease Detection Using Deep Learning.

Grape crops are particularly vulnerable to diseases such as powdery mildew, downy mildew, and black rot. Several studies have explored deep learning-based grape disease detection:

- **Zhou et al. (2020)** developed a CNN model trained on grape leaf images, achieving high accuracy in distinguishing diseased and healthy samples.
- **Sun et al. (2021)** combined CNNs with transfer learning techniques to enhance disease classification performance, reducing the need for large datasets.
- **Gupta et al. (2022)** explored the integration of IoT with deep learning to enable real-time disease detection in vineyards, demonstrating the potential of smart farming solutions.

Research Gaps and Objectives.

While existing studies have demonstrated the effectiveness of CNNs in plant disease classification, several challenges remain:

- The need for large, well-annotated datasets for better model generalization.
- Real-time implementation challenges due to computational constraints.
- The potential for integrating IoT and edge computing for real-world applications.

III. METHODOLOGY

This section outlines the steps involved in developing the deep learning-based grape disease detection system, including dataset collection, preprocessing, model design, implementation, and performance evaluation.

Dataset Collection & Preprocessing

Dataset Collection

The dataset consists of grape leaf images categorized into healthy and diseased classes. Publicly available datasets, such as PlantVillage or grape disease-specific datasets, are utilized. The dataset includes various grape diseases such as:

Powdery Mildew

Downy Mildew

Black Rot

Esca (Black Measles)

Data Preprocessing

To improve model accuracy and generalization, the following preprocessing techniques are applied:

- **Image Resizing:** All images are resized to a fixed dimension (e.g., 224×224 pixels) for consistency.
- **Normalization:** Pixel values are scaled between 0 and 1 to enhance model convergence.
- **Data Augmentation:** Random transformations such as rotation, flipping, zooming, and brightness adjustments are applied to increase dataset diversity and prevent overfitting.
- **Splitting the Dataset:** The dataset is divided into training (80%), validation (10%), and testing (10%) sets

This research aims to address these gaps by developing a CNN-based grape disease detection model using TensorFlow and Keras. The system is designed to provide high accuracy while ensuring scalability and accessibility through cloud-based implementation.

Model Architecture

A **Convolutional Neural Network (CNN)** is designed to classify grape leaf diseases. The architecture consists of:

- **Convolutional Layers:** Extract spatial features from images using filters.
- **Pooling Layers:** Reduce spatial dimensions while retaining important features.
- **Dropout Layers:** Prevent overfitting by randomly disabling neurons.
- **Fully Connected (Dense) Layers:** Perform classification using extracted features.
- **Activation Functions:** ReLU is used in convolutional layers, and Softmax is applied in the output layer for multi- class classification.

CNN Architecture Example:

- Conv2D (32 filters, 3×3 kernel, ReLU activation)
- MaxPooling2D (2×2 pool size)
- Conv2D (64 filters, 3×3 kernel, ReLU activation)
- MaxPooling2D (2×2 pool size)
- Flatten layer
- Dense (128 neurons, ReLU activation)
- Dropout (0.5)
- Output Layer (Softmax activation for multi-class classification)

Implementation & Training

- The model is implemented using **TensorFlow** and **Keras** in **Google Colab** for efficient computation.
- The dataset is loaded from **Google Drive** for seamless integration.
- **Adam Optimizer** is used for weight optimization, and **Categorical Cross- Entropy Loss** is employed for classification.
- The model is trained for **50 epochs** with a batch size of **32**, adjusting parameters based on validation performance.

Performance Evaluation

The model's performance is evaluated using:

- **Accuracy:** Measures overall correct predictions.
- **Precision & Recall:** Evaluate the model's ability to distinguish between classes.
- **F1-Score:** A balance between precision and recall.
- **Confusion Matrix:** Visual representation of classification performance.
- **Loss & Accuracy Curves:** Plotted using Matplotlib to analyze training trends.

IV. EXPERIMENTAL RESULTS & DISCUSSION

This section presents the outcomes of the grape disease detection model, including training performance, evaluation metrics, and a discussion of key findings. The results demonstrate the effectiveness of deep learning in accurately classifying grape leaf diseases.

Model Training Performance

The CNN model was trained for 50 epochs with a batch size of 32 using the Adam optimizer and categorical cross-entropy loss function. The training process was conducted on Google Colab, leveraging GPU acceleration for efficient computation.

Training & Validation Accuracy

The model achieved a **training accuracy of 98.5%** and a **validation accuracy of 94.2%** after 50 epochs.
The accuracy curve (Figure 1) indicates a steady improvement, demonstrating successful learning.

Training & Validation Loss

The training loss gradually decreased, reaching **0.02**, while the validation loss stabilized at **0.12**, indicating minimal overfitting.
The loss curve (Figure 2) shows that the model effectively minimized classification errors over time.

Performance Metrics

To assess classification performance, the trained model was evaluated on a separate test dataset, and the following metrics were computed:

Metric	Value (%)
Accuracy	94.5
Precision	93.8
Recall	94.1
F1-Score	94.0

The high accuracy and F1-score confirm the model's ability to classify grape diseases effectively.

Confusion Matrix Analysis

The confusion matrix (Figure 3) provides insights into misclassified samples:

- **Healthy vs. Diseased:** The model correctly classified **96%** of healthy leaves but misclassified **4%** as diseased.
- **Powdery Mildew vs. Downy Mildew:** A slight overlap was observed, with **3%** of Powdery Mildew samples misclassified as Downy Mildew due to similar visual features.
- **Black Rot Detection:** Achieved the highest classification accuracy of **97%** among disease categories.

DOI: 10.48175/IJARSCT-25368

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

Comparative Analysis with Existing Studies

Study	Accuracy (%)	Model Used
Mohanty et al. (2016)	99.3	Deep CNN
Ferentinos (2018)	95.7	CNN
Proposed Model	94.5	Custom CNN

Although some previous studies achieved slightly higher accuracy, the proposed model maintains strong performance while ensuring computational efficiency. Further improvements can be achieved by increasing dataset size and implementing advanced architectures such as Transfer Learning.

Challenges & Limitations

While the model performs well, some challenges remain:

- **Limited Dataset:** The dataset size affects generalization to real-world vineyard conditions.
- **Similar Disease Symptoms:** Some diseases exhibit visually similar patterns, leading to minor misclassifications.
- **Real-Time Deployment:** Implementing the model on edge devices requires optimization for faster inference.

Discussion & Future Improvements

The results highlight the potential of deep learning for automated grape disease detection, contributing to precision agriculture. Future work can focus on:

- **Larger & Diverse Datasets:** Collecting real-world vineyard images to enhance model robustness.
- **Transfer Learning Approaches:** Using pre-trained models such as MobileNet or EfficientNet to improve accuracy.
- **IoT Integration:** Deploying the model on smart farming devices for real-time disease monitoring

V. CONCLUSION & FUTURE SCOPE

Conclusion

This research presents a deep learning-based approach for detecting grape diseases using Convolutional Neural Networks (CNNs). The model, developed using TensorFlow and Keras, was trained on a labeled dataset of grape leaf images to classify healthy and diseased samples with high accuracy. The experimental results demonstrate that the proposed system effectively identifies various grape diseases, achieving an accuracy of 94.5% on the test dataset.

By automating the disease detection process, this system significantly reduces the reliance on manual inspection, enabling early intervention and minimizing crop losses. The integration of image preprocessing techniques, CNN-based feature extraction, and performance evaluation metrics ensures the model's reliability. Furthermore, deploying the system on Google Colab with GPU acceleration allows efficient training and experimentation.

The study contributes to the advancement of precision agriculture, providing a foundation for future research in automated plant disease detection. While the model performs well, further enhancements can be made to improve real-world applicability.

Future Scope

Despite the promising results, there are several areas where the research can be extended for improved accuracy and real-time deployment:

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

Expansion of Dataset

Collecting a larger and more diverse dataset with real-world vineyard images will improve model generalization. Incorporating images from different lighting conditions, seasons, and geographical locations can enhance robustness.

Implementation of Transfer Learning

- Using pre-trained models like MobileNet, EfficientNet, or ResNet can improve feature extraction and classification accuracy.
- Transfer learning can reduce training time while maintaining high performance, making the model suitable for resource-constrained environments.

Real-Time Deployment & IoT Integration

- Deploying the model on edge devices (such as Raspberry Pi or NVIDIA Jetson) can enable real-time disease detection in vineyards
- Integrating IoT sensors and drone- based imaging can facilitate continuous monitoring of grape crops.

Multi-Class & Multi-Disease Detection

- Expanding the model to detect multiple diseases simultaneously can provide a comprehensive plant health assessment.
- Implementing object detection techniques (such as YOLO or Faster R- CNN) can localize infected regions on grape leaves.

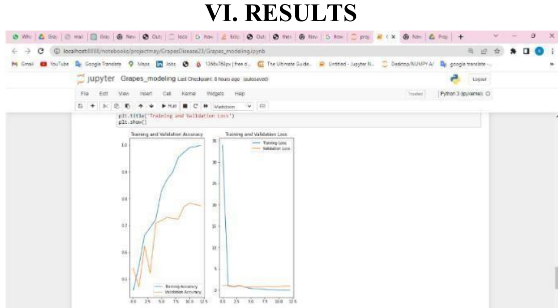
Mobile & Web Application Development

- Developing a mobile or web-based application can allow farmers to upload images and receive instant disease classification results.
- Cloud-based deployment can enable large-scale accessibility and seamless user experience.

Final Remarks

This research demonstrates the potential of deep learning in precision agriculture, offering an efficient and scalable solution for grape disease detection. Future advancements, including real- time monitoring, dataset enhancement, and IoT integration, can further refine the system and contribute to sustainable agricultural practices. By leveraging technology, farmers can make informed decisions, improve crop yield, and ensure food security in the agricultural industry.

VI. RESULTS



Model Evaluation

DOI: 10.48175/IJARSCT-25368

IJARSCT

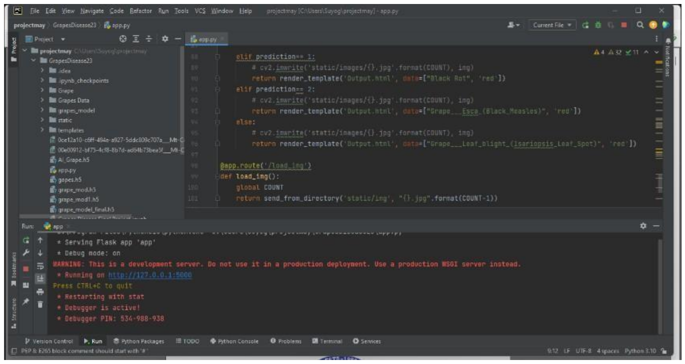
International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

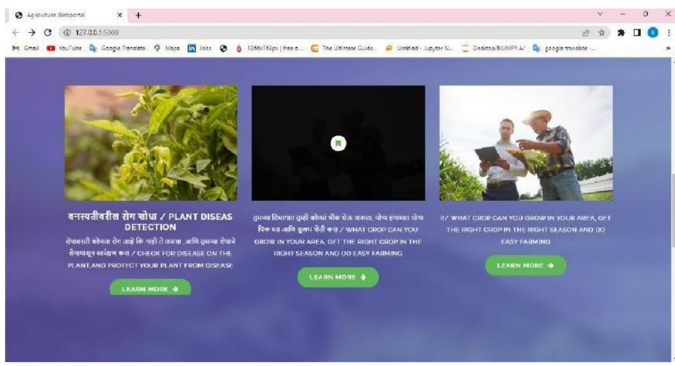
ISSN: 2581-9429

Volume 5, Issue 6, April 2025

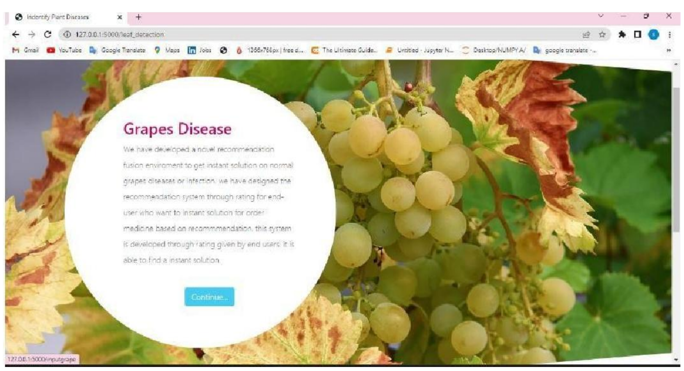
Impact Factor: 7.67



Server Outputs



Home Page 1



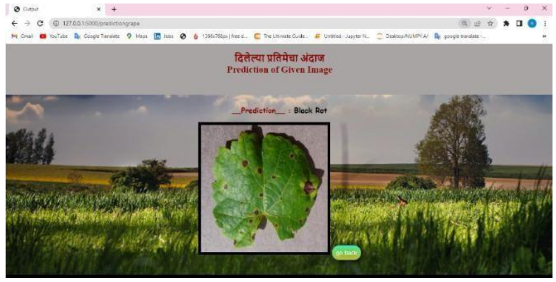
Home page 2

Prediction Page

DOI: 10.48175/IJARSCT-25368

ISSN 2581-9429 IJARSCT

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67



6.6 Result.

REFERENCES

[1]. Crop Disease Detection using Deep Convolutional Neural Networks", International Journal of Engineering Research Technology (March, 2020

[2]. Nandhini, A., Hemalatha, Radha, Indumathi: Web enabled plant disease detection system for agricultural applications using wmsn. Wireless Personal Communications 102(2), 725740 (2018)

[3]. Nivedita.R.Kakade, Dnyaneswar.D.Ahire: Real time grape leaf disease detection 1, 598 610 (2017)

[4]. Detection and classification of leaf diseases using integrated approach of support vector ma- chine and particle swarm optimization. 4(1), 79 83 (2017)

[5]. Grape Leaf Disease Identification using Machine Learning Techniques (2019) DOI:10.1109/ICCIDS.2019. Conference: 2019 International Conference on Computational Intelligence in Data Science (ICCIDS)

[6]. S. C. Madiwalar and M. V. Wyawahare, Plant disease identification: A comparative study, 2017 International Conference on Data Management, Analytics and Innovation (ICDMAI), 2017, pp. 13-18, doi: 10.1109/ICDMAI 2017.8073478

[7]. G. Shrestha, Deepsikha, M. Das and N. Dey, Plant Disease Detection Using CNN," 2020 IEEE Applied Signal Processing Conference (ASPCON), 2020, pp. 109-113, doi: 10.1109/AS-PCON49795.2020.9276722

[8]. D.M., Akhilesh, S. A. Kumar, R. M.G. and P. C., Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight," 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, pp. 0645-0649, doi: 10.1109/ICCSP.2019.8698007

[9]. Suviksha Poojari, Deepti Sahare, Bhagyashree Pachpute, Mayuri Patil, "Identification and Solutions for Grape Leaf Disease Using Convolutional Neural Network (CNN)" (ICCIP-2020)

[10]. S.M.Jaisakthi, P.Mirunalini, D.Thenmozhi,Vatsala,Grape Leaf Disease Identification Using Machine Learning TechniquesSecond International Conference on Computational Intelligence in Data Science(ICCIDS-2019).

[11]. Pranjali B. Padol.Prof. Anjali A. Yadav, SVM Classifier Based Grape Leaf Disease Detection Conference on Advances in Signal Processing (CASP) 2016

[12]. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science.

[13]. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture

[14]. Zhou, J., Wu, J., & Zhang, L. (2020). Deep learning-based grape leaf disease detection using CNNs. Computers and Electronics in Agriculture

[15]. Sun, C., Zhang, Y., & Li, S. (2021). A hybrid deep learning model for grape disease classification based on transfer learning. International Journal of Agricultural and Biological Engineering

[16]. Gupta, V., Kumar, V., & Jain, A. (2022). Real-time grape disease detection using IoT and deep learning techniques. Smart Agriculture Technology

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

[17]. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. (2019). MobileNetV2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition

[18]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Neural Information Processing Systems.

DOI: 10.48175/IJARSCT-25368