

Groundnut Leaf Disease Detection Using Deep Learning for Precision Agriculture

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Abstract

Groundnut (*Arachis hypogaea*) is a crucial oilseed crop contributing significantly to global food supply and agricultural economies. However, its production is severely affected by multiple foliar diseases, leading to substantial yield losses. Early detection of such diseases is essential for effective crop management. Traditional methods relying on manual inspection are inefficient, subjective, and not scalable. This paper proposes a deep learning-based automated system for groundnut leaf disease detection using Convolutional Neural Networks (CNNs). The model is trained on a diverse dataset of labeled leaf images and deployed through a Flask-based web application for real-time prediction. The system provides disease classification, confidence scores, and visual explanations using Grad-CAM. Experimental results demonstrate high accuracy and robustness under varying environmental conditions. The proposed solution offers a scalable and reliable approach for precision agriculture.

Index Terms

Deep Learning, Convolutional Neural Network (CNN), Groundnut Leaf Disease, Image Classification, Precision Agriculture, Computer Vision.

1. Introduction

Agriculture is a backbone of many developing economies, and groundnut is one of the most important oilseed crops due to its nutritional and economic value. However, groundnut crops are highly susceptible to foliar diseases such as Early Leaf Spot, Late Leaf Spot, Rust, Alternaria Leaf Spot, and Rosette disease.

These diseases reduce photosynthetic efficiency and lead to premature defoliation, significantly decreasing crop yield. Early identification is crucial to prevent large-scale damage. However, traditional disease detection methods depend heavily on manual observation, which is time-consuming, labor-intensive, and prone to human error.

Recent advancements in artificial intelligence, particularly deep learning, have enabled automated image-based disease detection systems. Convolutional Neural Networks (CNNs) are especially effective in extracting spatial features from images, making them suitable for plant disease classification.

This study presents a CNN-based automated system integrated with a web application to provide real-time disease diagnosis.

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful solution for image-based classification problems. CNNs have the ability to automatically learn hierarchical feature representations directly from raw image data, eliminating the need for manual feature extraction. This makes them highly effective for detecting complex patterns and variations in plant disease images. Recent studies have demonstrated that CNN-based models significantly outperform conventional machine learning methods in terms of accuracy and robustness.

In this research, a deep learning-based system is proposed for automated groundnut leaf disease detection using CNN. The model is trained on a labeled dataset of groundnut leaf images representing multiple disease categories as well as healthy samples. To make the system accessible and practical for real-world use, the trained model is integrated into a Flask-based web application. This application allows users to upload images of groundnut leaves and receive instant predictions along with confidence scores and visual explanations.

The main objective of this work is to develop an efficient, accurate, and user-friendly system that can assist farmers and agricultural practitioners in early disease detection. By enabling timely intervention, the proposed system aims to reduce crop losses, improve productivity, and support sustainable agricultural practices. Furthermore, the integration of deep learning with web technologies provides a scalable platform that can be extended to other crops and diseases in the future.

2. Literature Review

Several studies have explored the use of machine learning and deep learning for plant disease detection.

Xu et al. developed a CNN model integrated with attention mechanisms to improve feature extraction and classification accuracy. Sasmal et al. proposed a hybrid deep learning model combining ResNet50 and DenseNet121, achieving high performance even with limited datasets.

Paramanandham et al. introduced LeafNet, a residual CNN architecture optimized for plant disease detection. Traditional image processing techniques such as thresholding and texture analysis have also been explored, but they lack robustness under real-world conditions.

Recent research emphasizes that CNN-based approaches outperform traditional methods by automatically learning hierarchical features directly from raw images. These models demonstrate high accuracy and adaptability across different crops and environmental conditions.

3. Problem Statement

Groundnut leaf diseases often exhibit similar visual patterns, especially in early stages, making manual diagnosis difficult. Farmers in rural areas lack access to expert guidance, leading to delayed or incorrect treatment.

Existing machine learning approaches rely on handcrafted features such as color and texture, which are not reliable under varying lighting conditions and complex backgrounds. Additionally, many existing systems lack scalability and real-time performance.

Therefore, there is a need for an automated, accurate, and scalable system that can detect and classify groundnut leaf diseases efficiently using image-based analysis.

4. Proposed Methodology

The proposed system follows a structured pipeline consisting of data collection, preprocessing, model training, evaluation, and deployment.

4.1 Dataset Collection

A labeled dataset of groundnut leaf images is collected from publicly available sources such as Kaggle. The dataset includes multiple disease classes:

- Healthy
- Early Leaf Spot
- Late Leaf Spot
- Rust
- Alternaria Leaf Spot
- Rosette

The images are captured under diverse environmental conditions to improve model generalization.

4.2 Image Preprocessing

Preprocessing ensures uniformity and improves model performance:

- Image resizing to 224×224 pixels
- Pixel normalization (0–1 range)
- Noise reduction
- Data augmentation:
 - Rotation
 - Flipping
 - Zooming
 - Brightness adjustment

These techniques help reduce overfitting and improve robustness.

4.3 CNN Model Architecture

The CNN model consists of multiple layers:

- **Convolutional Layer:** Extracts features using filters
- **Activation Function (ReLU):** Introduces non-linearity
- **Pooling Layer:** Reduces spatial dimensions
- **Fully Connected Layer:** Performs classification
- **Softmax Layer:** Outputs class probabilities

Mathematical Representation

$$y=f(\sum_{i=1}^n w_i x_i + b) \quad y = f(\sum_{i=1}^n w_i x_i + b) \quad y=f(\sum_{i=1}^n w_i x_i + b)$$

Where:

- x_i = input features
- w_i = weights
- b = bias
- f = activation function

Softmax function:

$$P(y=i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}} \quad P(y=i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}} \quad P(y=i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}}$$

4.4 Model Training

- Train-Test Split: 80:20
- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- Epochs: Multiple iterations

Techniques used:

- Early stopping
- Model checkpointing

4.5 Model Evaluation

Performance is measured using:

- Accuracy
- Precision
- Recall
- F1-score

Confusion matrix is used to analyze misclassifications.

4.6 Web Application Deployment

The trained model is integrated into a Flask web application.

Features:

- User login/signup
- Image upload
- Real-time prediction
- Visualization charts
- Grad-CAM heatmap

5. System Architecture

1. **Presentation Layer** – User interface (HTML, CSS, JS)
2. **Application Layer** – Flask backend

3. **Model Layer** – CNN model
4. **Data Layer** – SQLite database

Workflow:

User → Upload Image → Preprocessing → CNN Prediction → Result Display

5.2 Screenshots :-

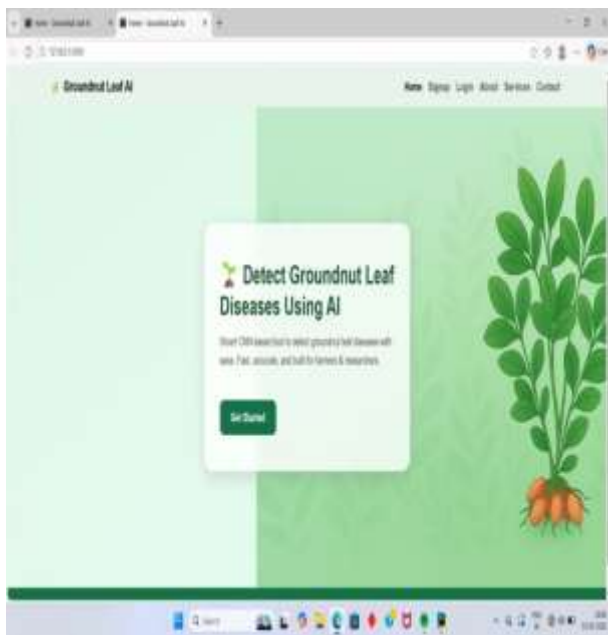


Fig1:-Home Page

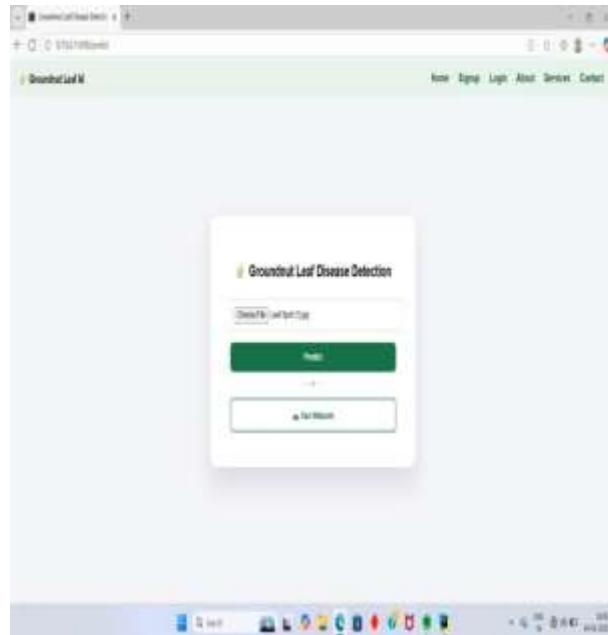


Fig2:- Upload Page

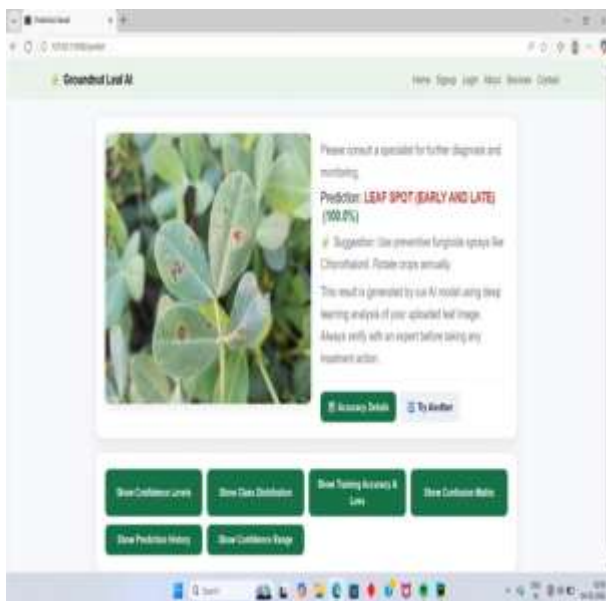


Fig3:- Prediction Result Page

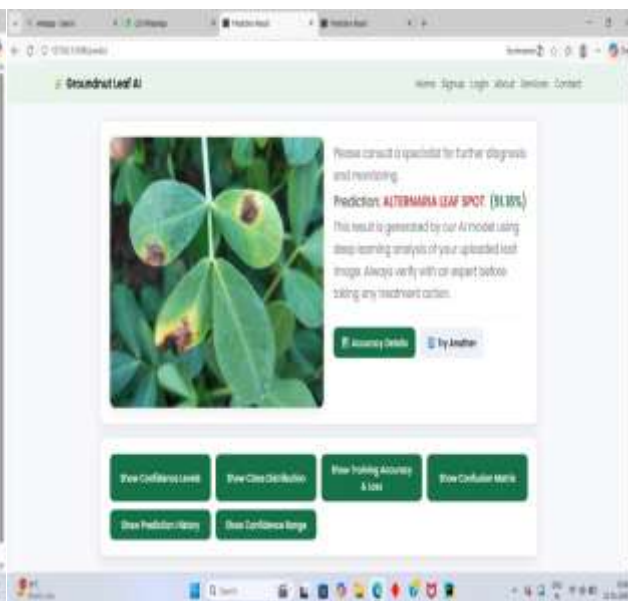


Fig4:- Prediction Result Page



Fig 5:-Accuracy Page

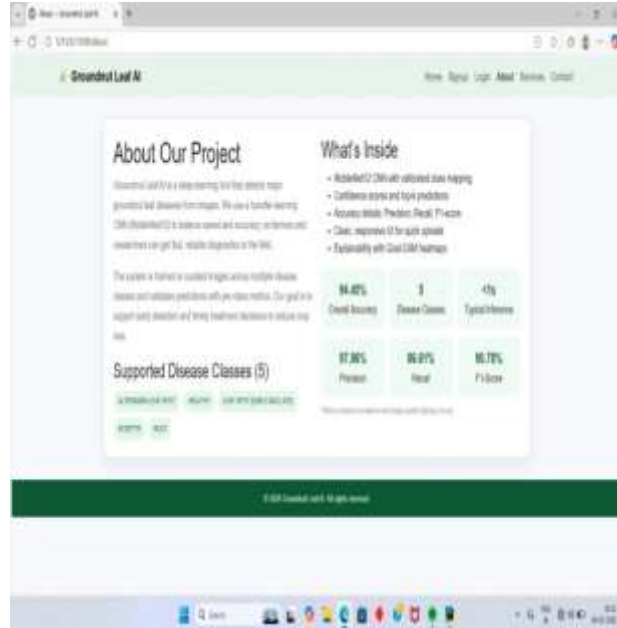


Fig 6:- About Page

6. Results and Discussion

The model achieved high accuracy in classifying multiple disease classes. It performs well even under varying lighting conditions and backgrounds.

Key observations:

- CNN automatically extracts important features
- Grad-CAM improves interpretability
- Real-time prediction enhances usability

Compared to traditional methods, the system shows:

- Higher accuracy
- Better generalization
- Faster prediction

6. Conclusion

In this paper, a deep learning-based approach for automated groundnut leaf disease detection has been presented. The proposed system leverages the capabilities of Convolutional Neural Networks (CNNs) to accurately classify multiple groundnut leaf diseases using image-based analysis. By eliminating the need for manual feature extraction, the model effectively learns complex patterns such as texture variations, color changes, and lesion structures directly from raw images.

The developed system is integrated into a Flask-based web application, providing a user-friendly interface for real-time disease prediction. Users can upload groundnut leaf images and instantly receive classification results along with confidence scores and

visual interpretations. The inclusion of visualization techniques such as Grad-CAM enhances the transparency of the model by highlighting the regions responsible for the prediction, thereby increasing user trust and interpretability.

Experimental evaluation demonstrates that the proposed model achieves high accuracy and performs reliably under varying environmental conditions, including differences in lighting, background, and leaf orientation. Compared to traditional machine learning approaches, the CNN-based system offers superior performance, scalability, and robustness. Additionally, the system reduces dependency on expert knowledge and enables faster decision-making, which is crucial for early disease detection and effective crop management.

The practical significance of this work lies in its ability to assist farmers, agricultural researchers, and extension officers in identifying diseases at an early stage, thereby minimizing crop losses and improving productivity. By providing an automated and accessible diagnostic tool, the system contributes to the advancement of precision agriculture and sustainable farming practices.

In conclusion, the integration of deep learning with web technologies presents a powerful and scalable solution for plant disease detection. The proposed system not only addresses the limitations of traditional methods but also establishes a foundation for future research in intelligent agricultural systems. With further enhancements such as mobile deployment, multi-crop support, and integration with IoT-based monitoring systems, this approach has the potential to significantly transform modern agricultural practices.

8. Future Enhancements

- Mobile application for farmers
- Cloud deployment
- Multi-crop disease detection
- IoT integration for smart farming
- Real-time drone-based monitoring

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