DEPARTMENT OF INFORMATION SCIENCE & ENGINEERING

PROJECT (21ISP76)

PLANT LEAF DISEASE DETECTION USING CNN & ALEXNET MODEL

Presented by:

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ABSTRACT

Plant diseases pose a significant threat to agricultural productivity, food security, and economic stability. Early and accurate detection of plant diseases is crucial for effective disease management and prevention. This project leverages Artificial Intelligence (AI) and Machine Learning (ML) to develop an automated plant disease detection system using image classification techniques.

CONTENTS

INTODUCTION

Agricultural Impact of Plant Diseases: Plant diseases pose significant challenges to agriculture by affecting crop productivity, food security, and economic stability.

Importance of Early Detection: Early and accurate detection is crucial for effective disease management and prevention.

Project Overview: This project utilizes machine learning, focusing on Convolutional Neural Networks (CNN) and the AlexNet architecture, to create an automated system for detecting plant diseases.

INTODUCTION

Methodology: The system analyzes images of plant leaves to detect diseases with accuracy.

Solution Goal: By identifying diseases early and suggesting specific treatments, the system aims to support farmers in managing plant health.

Advantages for Farmers: This tool is designed to be low-cost, fast, and reliable, making it accessible and beneficial for farmers.

PROBLEM STATEMENT

Farmers traditionally **rely on manual** observation or expert advice for detecting plant diseases. Manual methods are **time-consuming, error-prone**, and may require **expert knowledge** that is not always available. Hence, there is a need for an **automated and scalable** solution to detect plant diseases effectively.

OBJECTIVES

- **To develop a machine learning model** that can detect and classify plant diseases using images of plant leaves.
- Provide a **fast and reliable** solution for farmers and agricultural experts.
- Improve **agricultural productivity** by identifying diseases in early stages.
- Offer **disease-specific prescriptions** and recommendations to help farmers manage and treat affected plants effectively.

HARDWARE AND SOFTWARE REQUIREMENTS

Hardware Requirements:

Processor:

- Intel Core i5 or higher (preferably i7 or i9 for faster processing).
- AMD Ryzen 5 or higher.

GPU (Optional but Recommended for Faster Training):

- NVIDIA GPU with CUDA support (e.g., NVIDIA GTX 1060 or higher).
- At least 4GB VRAM for moderate performance, 8GB or higher for optimal results.

HARDWARE AND SOFTWARE REQUIREMENTS

Memory (RAM):

- Minimum 8GB (16GB or higher recommended for smooth processing).

Storage:

- SSD with at least 256GB for system files and software
- Additional storage (HDD or SSD) for dataset, ideally 1TB.

Camera (For Image Capture):

- High-resolution camera for capturing plant images (mobile cameras with good resolution can work as well).

HARDWARE AND SOFTWARE REQUIREMENTS

Software Requirements:

Operating System:

- Windows 10 or higher, MacOS, or Linux (Ubuntu recommended for compatibility with machine learning libraries).

Programming Language:

- Python 3.x

Development Environment and Libraries:

- Jupyter Notebook or any Python IDE (e.g., PyCharm, VS Code).
- Machine learning libraries: TensorFlow or PyTorch, Keras for model building.

HARDWARE AND SOFTWARE REQUIREMENTS

Additional Libraries and Tools:

- NumPy, Pandas, and Matplotlib for data manipulation and visualization.
- Scikit-learn for model evaluation metrics.

Web Application Framework:

- Streamlit for building an interactive and user-friendly web app interface.

EXISTING SYSTEM

Basic Mobile Apps:

- Use simple image processing, often lacking accuracy and robustness.
- Struggle under different environmental conditions, with limited disease-specific advice.

Challenges in Scale and Precision:

- Existing systems are limited in scale and often detect only a few diseases.
- Generally lack disease-specific prescriptions and accuracy.
- The accuracy is often low, with many systems providing generic suggestions rather than disease-specific prescriptions.

PROPOSED SYSTEM

The proposed system leverages Convolutional Neural Networks (CNN), specifically using AlexNet and ResNet models, to create an automated, reliable, and accurate plant disease detection tool. Key components and features include:

Image Classification and Feature Extraction:

- Uses CNN models to analyze plant leaf images and identify disease features.
- AlexNet for classification and ResNet for higher accuracy in detecting specific diseases.

PROPOSED SYSTEM

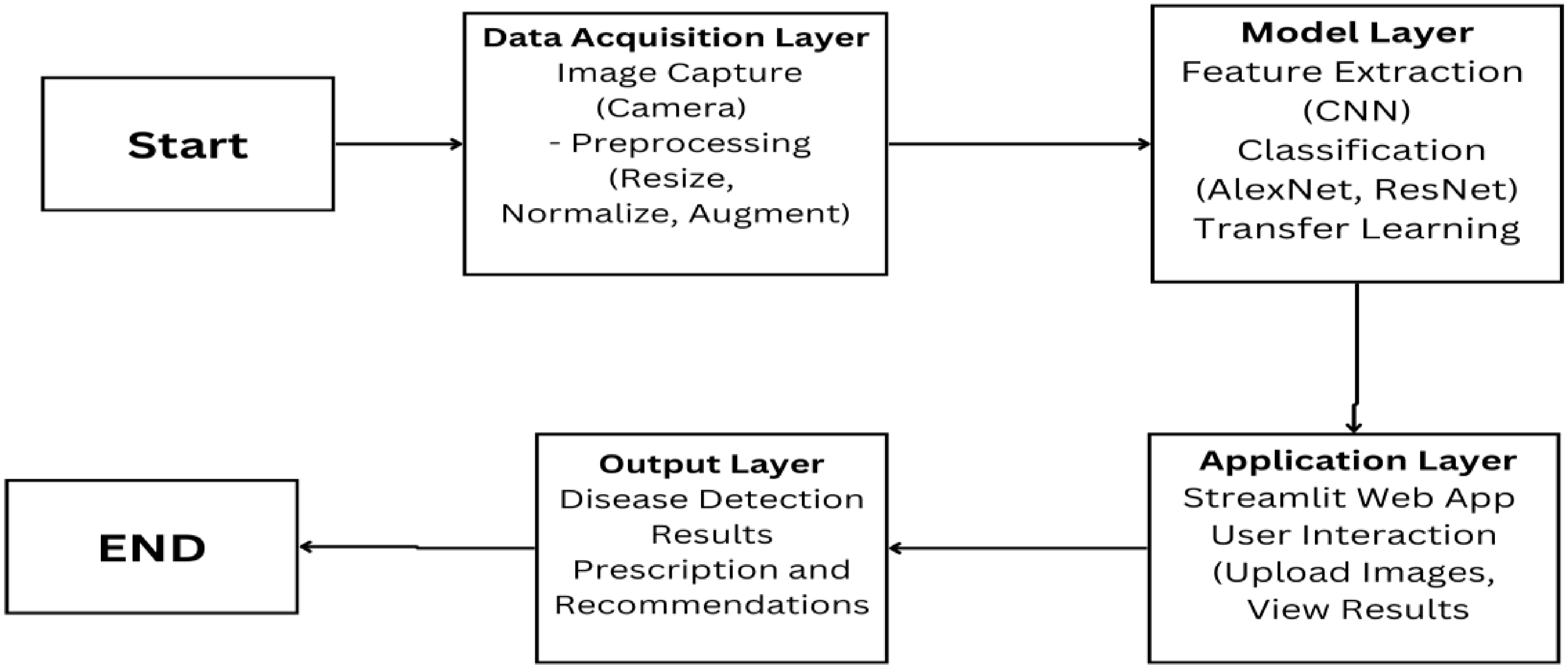
Real-Time Detection and Prescription:

- Integrates with a Streamlit-based web application allowing users to upload images and receive real-time diagnosis and treatment recommendations.

Advantages:

- High Accuracy: Detects a wide range of diseases with minimal errors.
- Scalability: Suitable for large-scale farming without the need for experts.
- Cost-effective: Provides a low-cost solution, accessible for farmers in rural and remote areas.

SYSTEM ARCHITECTURE



SYSTEM ARCHITECTURE

1. Data Acquisition Layer:

- Input: Collects plant leaf images from sources like mobile devices, cameras, or image datasets (e.g., PlantVillage).
- Preprocessing: Resizes, normalizes, and augments images to improve model accuracy and handle varied environmental conditions.

2. Model Layer:

- Feature Extraction: Uses a Convolutional Neural Network (CNN) to detect disease-specific features in leaf images.
- Classification: Utilizes AlexNet and ResNet models for high-accuracy classification of plant diseases.
- Transfer Learning: Employs pre-trained model layers for faster and more accurate learning, reducing training time.

SYSTEM ARCHITECTURE

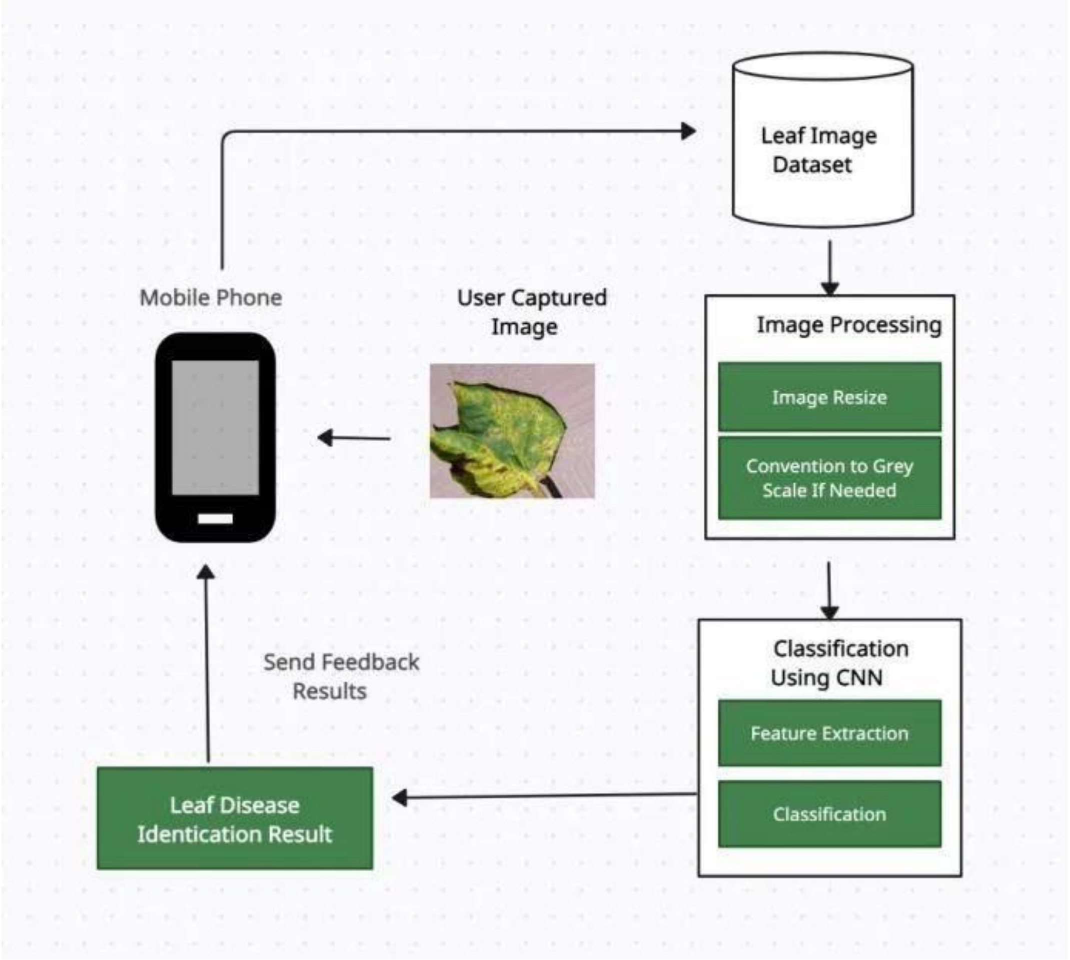
3. Application Layer:

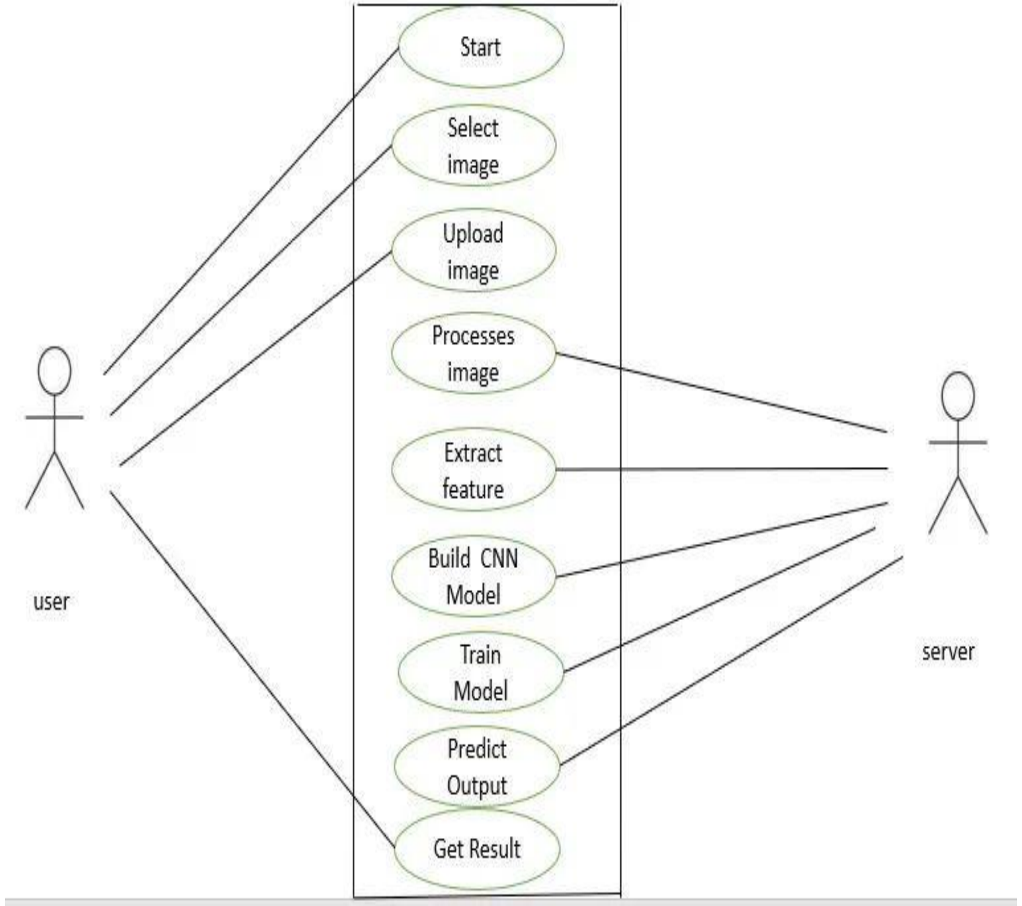
- Web Interface: A Streamlit-based app that enables users to upload leaf images for real-time disease diagnosis.
- User Interaction: Allows farmers and agricultural experts to view results, receive prescriptions, and access treatment recommendations.

4. Output Layer:

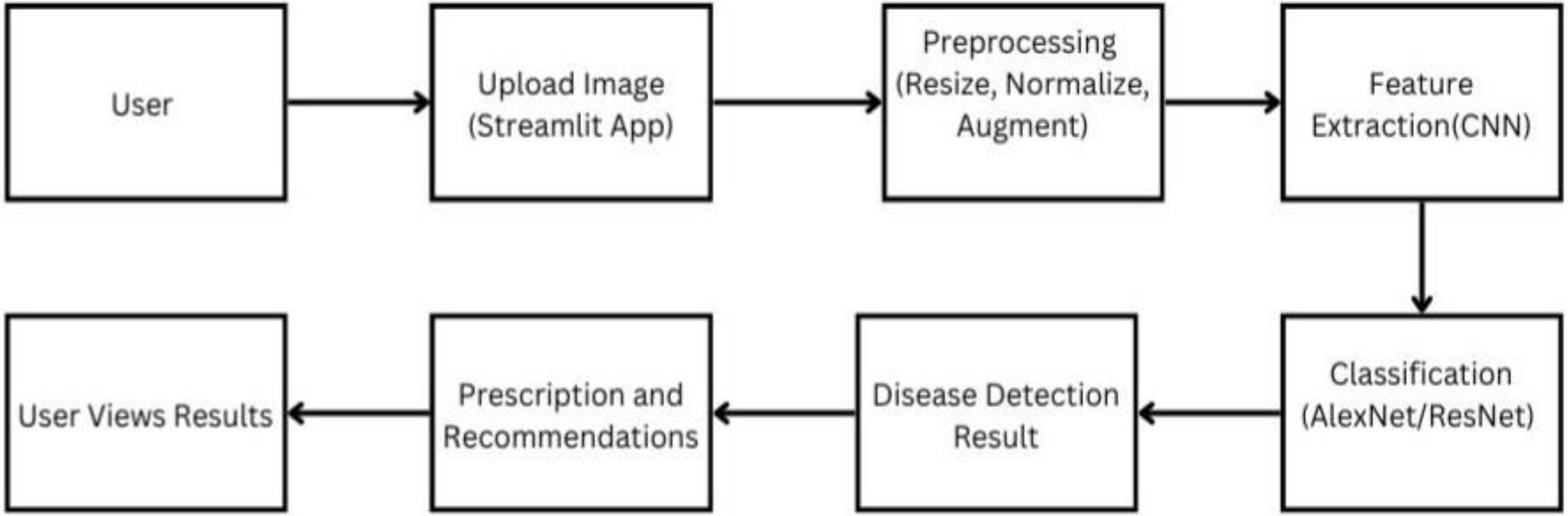
- Disease Detection Result: Displays the detected disease type along with confidence levels.
- Prescription and Recommendations: Provides disease-specific management steps, guiding farmers on treating the identified disease.

USE CASE DIAGRAM

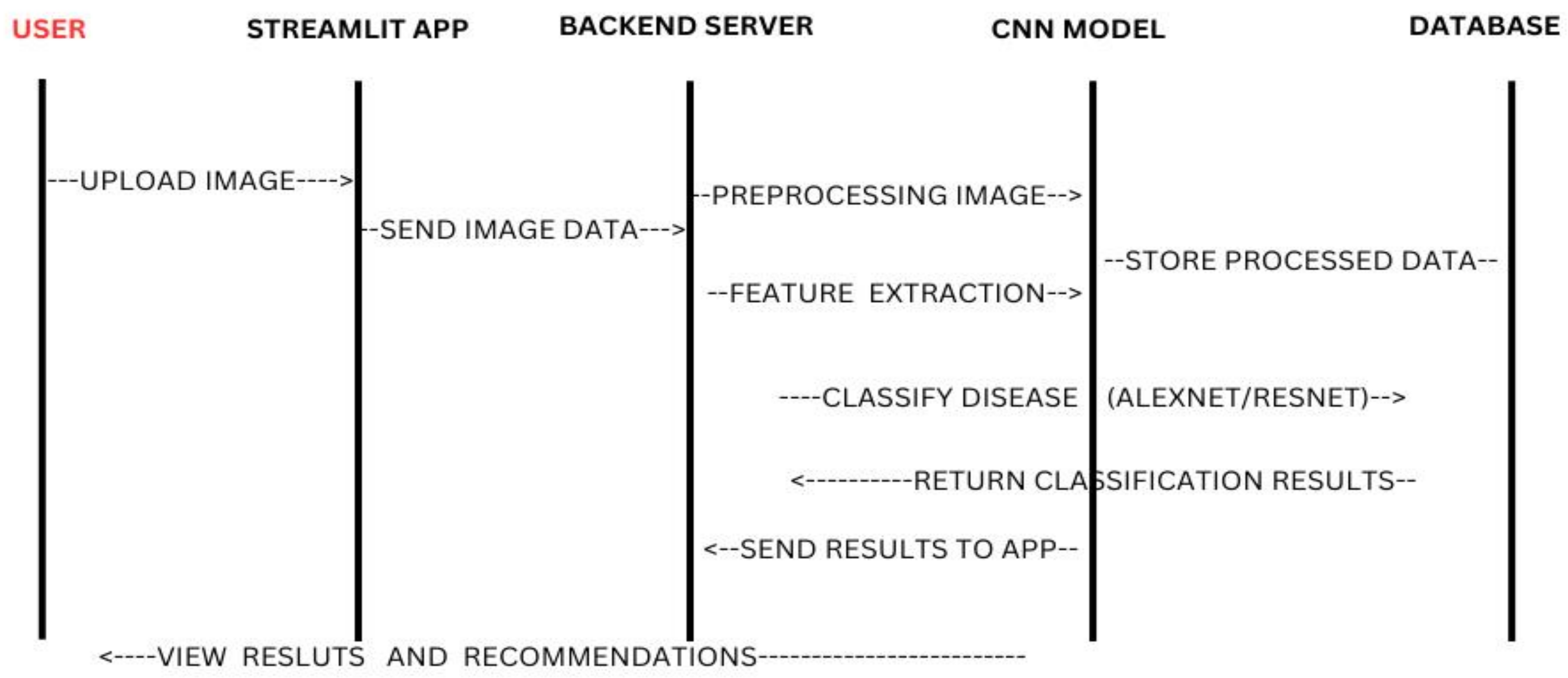




DATA FLOW DIAGRAM



SEQUENCE DIAGRAM



IMPLEMENTATION

1. Data Collection and Preparation:

- Gather plant leaf images (healthy and diseased) from datasets like PlantVillage.
- Preprocess images (resize, normalize, augment) and split into training, validation, and test sets.

2. Model Development:

- Feature Extraction (CNN): Capture disease patterns from images.
- Classification (AlexNet/ResNet): Use these models to classify diseases accurately.
- Evaluation: Assess model performance using accuracy and precision metrics.

IMPLEMENTATION

3. Web Application & Deployment:

- Web App Development (Streamlit)
- Create a user-friendly interface for image upload, detection results, and recommendations.
- Integrate model into Streamlit for real-time predictions.

4. Deployment & Monitoring:

- Deployment: Use cloud services (AWS, Heroku) for scalability.
- Feedback & Retraining: Gather user feedback and periodically update the model.
- System Maintenance: Regularly update the app and backend for security and performance.

TESTING

1. Unit Testing:

- Model Components: Test individual model components (e.g., CNN layers, feature extraction) to verify they work correctly.
- Data Processing: Check preprocessing functions (resize, normalization, augmentation) to ensure data consistency.

2. Model Evaluation and Validation:

- Accuracy Testing: Evaluate model accuracy using the test dataset, assessing metrics like accuracy, precision, recall, and F1-score.
- Cross-Validation: Perform k-fold cross-validation to ensure consistent performance across data subsets.

TESTING

- Confusion Matrix Analysis: Analyze true positives, false positives, etc., to identify any patterns of misclassification.

3. Integration Testing:

- Model and Web App: Test integration of the model with the Streamlit app, verifying seamless image upload, processing, and result display.
- Backend Communication: Ensure the app communicates effectively with the backend server for real-time predictions.

RESULTS AND DISCUSSION

Results:

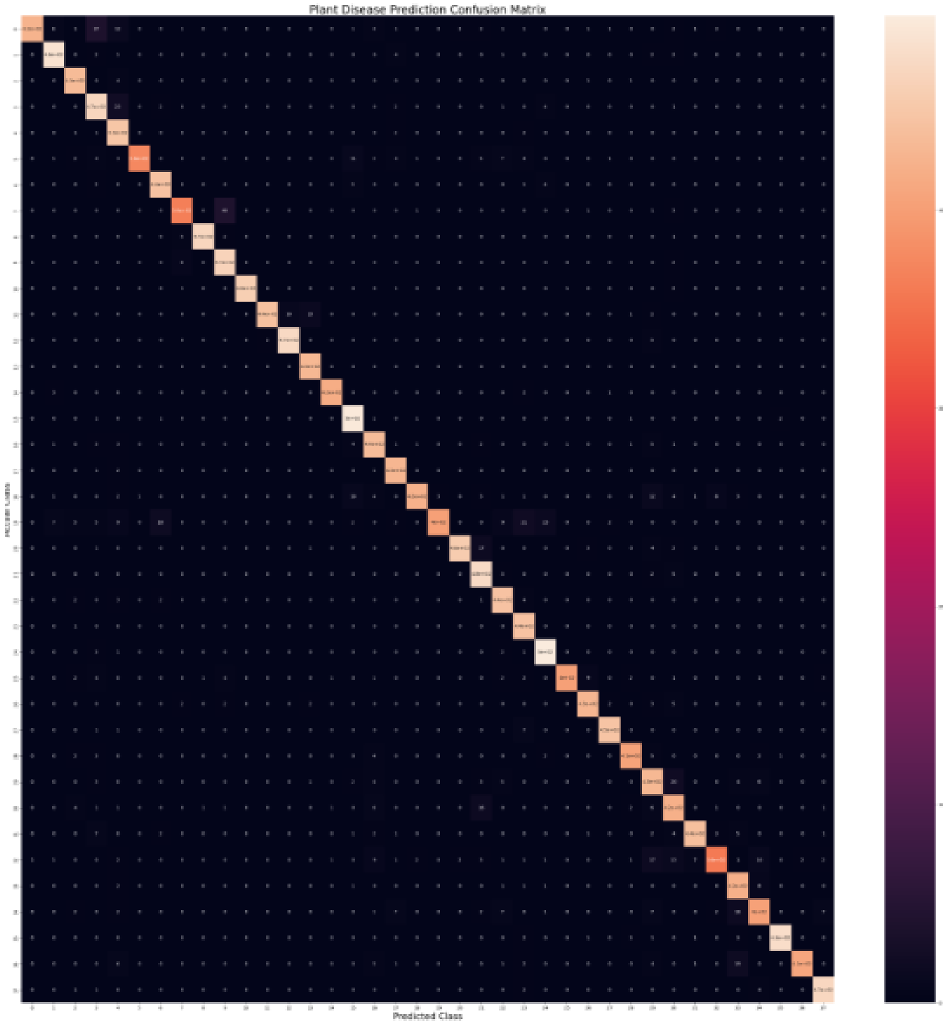
Model Functionality:

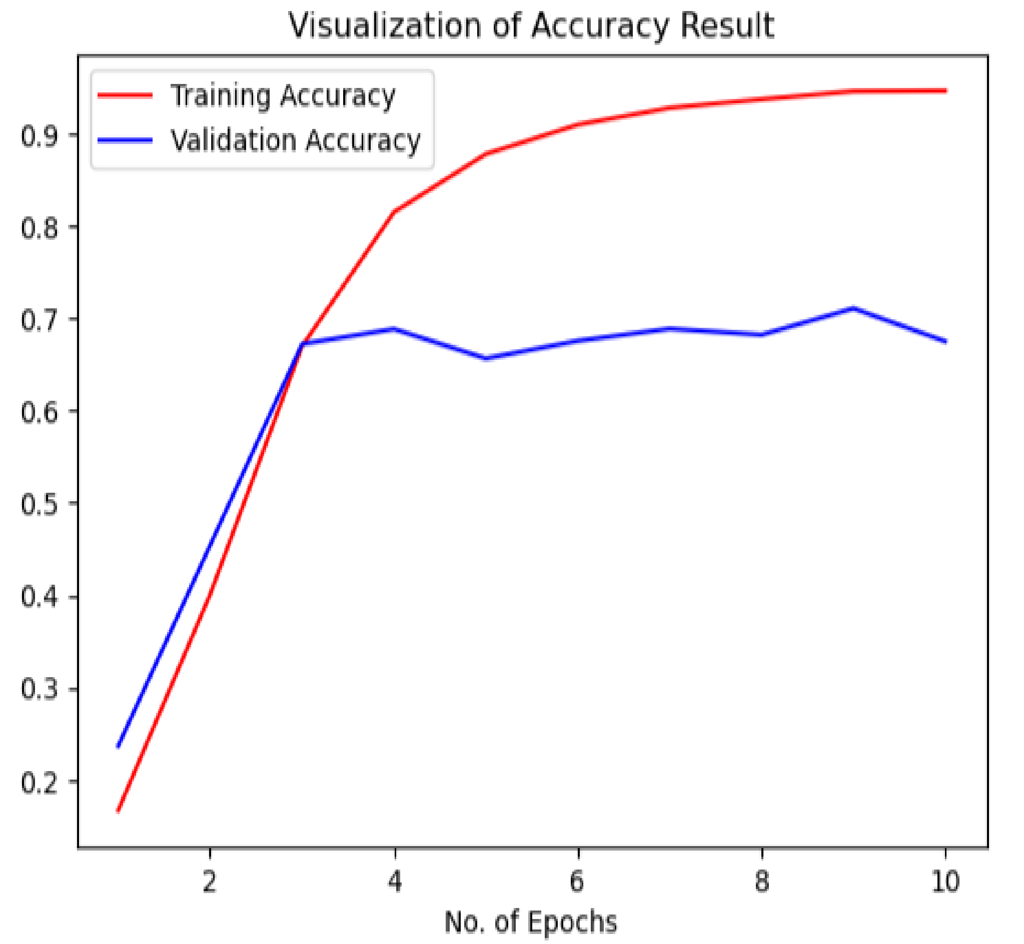
- The developed model accurately predicts plant diseases and provides specific prescriptions based on uploaded images.
- It also supports batch processing, allowing multiple images to be analyzed simultaneously, enhancing usability for farmers and agricultural experts.

Performance:

• If metrics like accuracy or precision are available, they should be listed to highlight the model's effectiveness. Emphasize any notable strengths in detecting a wide range of diseases or handling multiple images efficiently.

RESULTS AND DISCUSSION





RESULTS AND DISCUSSION

Discussion:

Interpretation of Results:

- This model's dual functionality disease detection and prescription generation directly aids in proactive plant health management, giving users immediate, actionable insights.
- Multi-image analysis adds practical value by enabling the assessment of large-scale crop data in one session, saving time and improving efficiency.

Limitations:

- Potential limitations include challenges in recognizing less common diseases or providing highly customized prescriptions, especially in diverse environmental conditions.

RESULTS AND DISCUSSION

Implications and Future Work:

- This tool has real-world impact potential, supporting farmers with timely diagnoses that could increase crop yields and reduce costs.
- Future work might focus on expanding the disease database, refining the prescription suggestions, and enhancing adaptability to various agricultural environments.

FUTURE SCOPE

- **Expanded Disease Database**: Include a wider range of plant diseases across various crop types for increased versatility.
- **Improved Prescription Precision**: Integrate real-time data (e.g., weather, soil health) to provide more accurate, context-specific recommendations.
- **Mobile and Offline Access**: Develop a mobile app with offline functionality to support farmers in areas with limited internet connectivity.
- **Multi-Language Support**: Add multiple language options to make the tool accessible to diverse user groups in various regions.

CONCLUSION

Model Capabilities: The model accurately identifies plant diseases from uploaded images and provides targeted prescriptions to help users address crop health issues efficiently.

Multi-Image Analysis: It can analyze multiple images simultaneously, making it suitable for large-scale agricultural use.

Practical Benefits: The tool aids farmers and agricultural experts in making quick, data-driven decisions.

Key Advantages: The model offers reliable, fast, and accessible disease detection, supporting real-world agricultural productivity and minimizing crop losses.

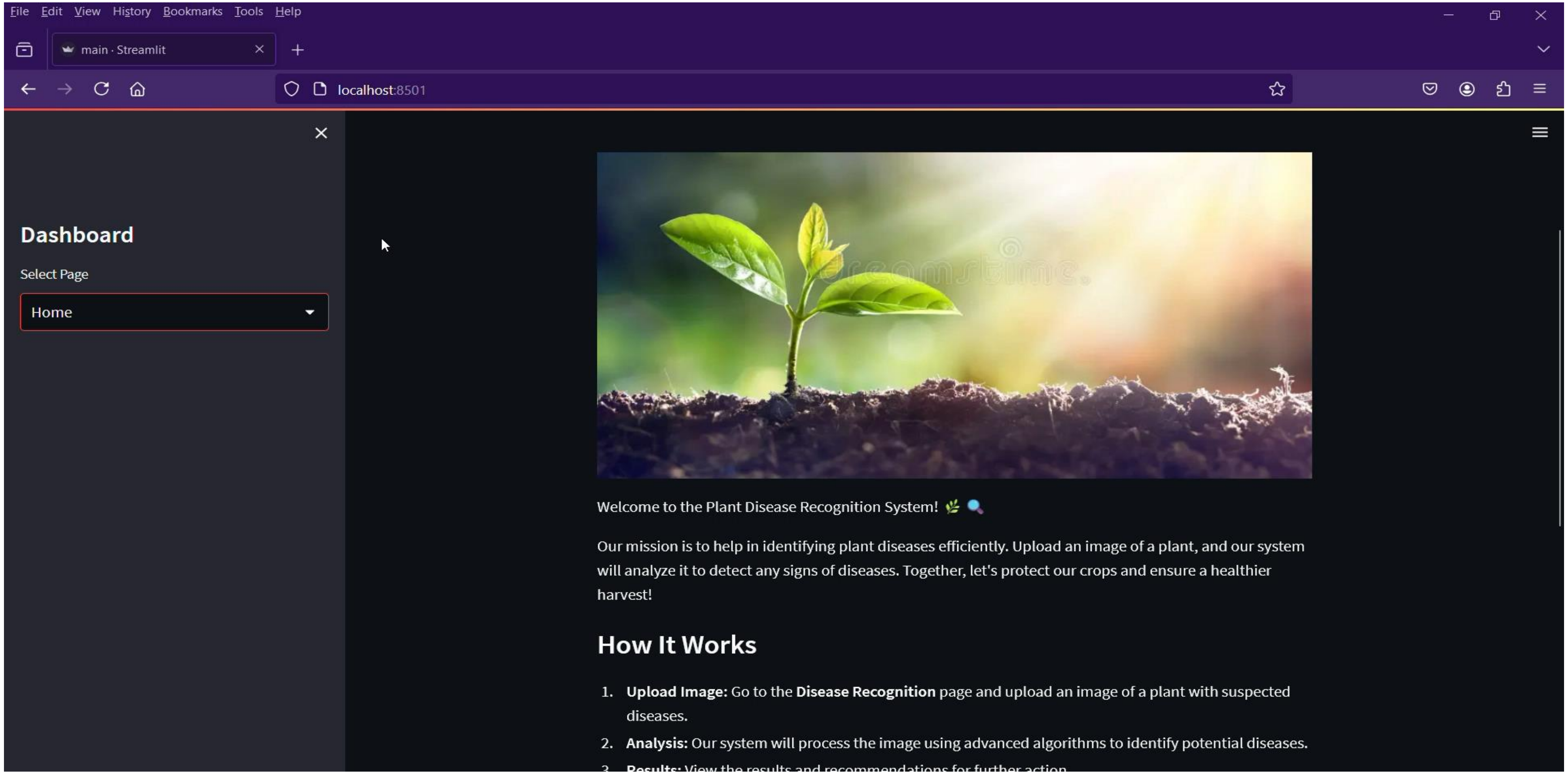
CONCLUSION

Future Enhancements:

- Expansion of the disease database to cover more plant diseases.
- Development of mobile compatibility for wider accessibility.
- Integration of real-time monitoring capabilities to enhance usability.

Sustainable Farming Impact: This tool has the potential to contribute to sustainable farming practices by improving productivity and reducing agricultural losses.

DEMO OF THE PROJECT



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THANK YOU