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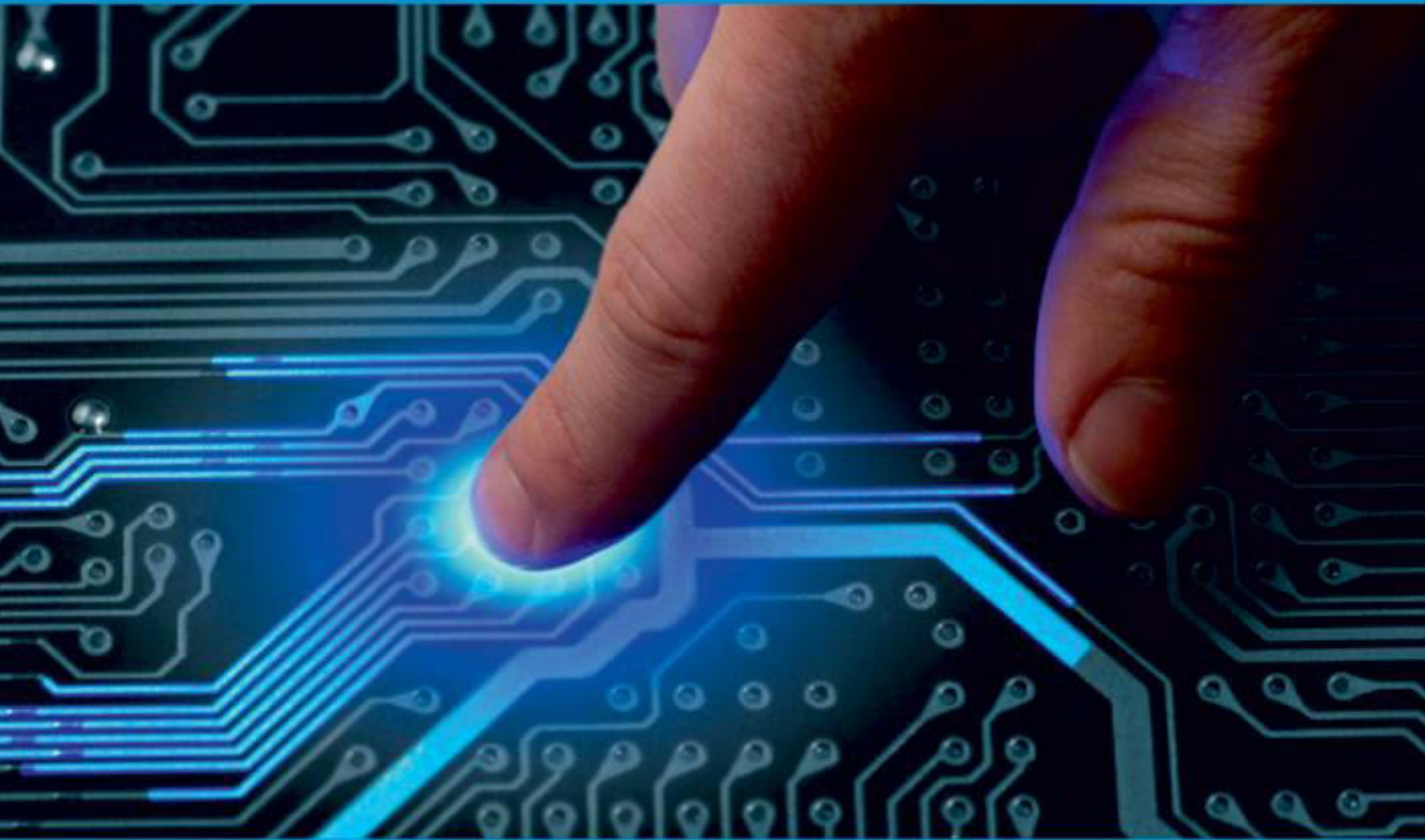

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AgriVision System: Early Detection of Crop Diseases and Classification to Crop Care using CNN for Smart Farming

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ABSTRACT: Crop diseases pose a significant challenge to global agricultural productivity and food security. Early detection and classification of diseases are vital for effective management and mitigation. This study focuses on a deep learning-based model for crop disease classification, implemented using Convolutional Neural Networks (CNN). Leveraging image data, the model achieves high accuracy in identifying key diseases affecting crops, offering a scalable and reliable solution for farmers and agricultural stakeholders. This research emphasizes the methodology, dataset utilization, model performance, and future prospects for deploying CNNs in agricultural applications. This paper outlines an innovative methodology for monitoring crop health through an automated and precise plant disease detection system. The approach leverages advanced image processing techniques, including Image Processing and deep learning, to identify diseased plants at an early stage. The primary aim is to enhance agricultural productivity by enabling timely interventions.

KEYWORDS: Crop Diseases Detection, Early Detection, Disease Classification, Deep Learning, CNN, Image Data, Model Accuracy, Agricultural Stakeholders, Scalable Solutions, Reliable Solutions, Dataset Utilization, Model Performance.

I. INTRODUCTION

Agriculture is a key part of the global economy, and crops are one of the most commonly grown plants worldwide. However, diseases like late blight, early blight, and bacterial wilt can greatly reduce both the quantity and quality of crops. Traditional methods of identifying these diseases take a lot of time, rely on expert knowledge, and are often too complicated or expensive for small-scale farmers to use. Recent advancements in technology, especially in deep learning using Convolutional Neural Networks (CNNs), have made it possible to classify diseases in images automatically. This research uses CNNs to detect crop diseases accurately and efficiently. By analyzing images of crops, the model provides a quick and reliable way to identify diseases, offering a modern solution to help farmers manage and protect their crops.

II. LITERATURE REVIEW AGRI VISION SYSTEM USING CNN FOR SMART FARMING

2.1 Crop Diseases and Pests Detection Using Convolutional Neural Network: The study leverages Convolutional Neural Networks (CNNs) and transfers learning to develop an efficient system for detecting crop diseases and pests, aiming to enhance crop productivity. It employs methodologies like image preprocessing, classification, and fine-tuning pre-trained models, achieving accuracy above 90%. However, challenges include limited real-world testing, dataset biases toward lab images, and a focus on leaf-based detection, restricting practical applicability to diverse farming environments and conditions.

2.2 Disease Detection using Machine Learning: This title reflects the focus of the paper on utilizing machine learning techniques to identify and classify diseases affecting crops, highlighting the intersection of agriculture and technology.

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The study leverages machine learning (ML) and deep learning (DL) for early detection and classification of crop diseases, aiming to improve agricultural productivity. It integrates tools like Node MCU for data transmission and Convolutional Neural Networks (CNNs) for analyzing and classifying leaf images. The approach emphasizes real-time disease monitoring, efficient processing, and user satisfaction. However, challenges include the need for high-quality datasets, environmental variability (e.g., lighting and orientation), and scalability issues for large agricultural deployments. The system aims to deliver accurate and timely results, with the potential to assist farmers in better decision-making while addressing practical implementation hurdles in real-world scenarios.

2.3 Prediction Analysis and Plant Disease Detection Using Machine Learning: This project integrates machine learning (ML) and deep learning (DL) to revolutionize agriculture in India, focusing on crop recommendation, fertilizer recommendation, and plant disease detection. It employs data collection, preprocessing, and ML models like Random Forest and XGBoost, achieving up to 98% accuracy. A web-based platform ensures user accessibility. Challenges include ensuring high-quality datasets, managing model complexity, and engaging non-technical users. The initiative addresses crop yields, soil properties, and disease classification, aiming to empower farmers with precise recommendations while improving resource use and productivity. Integration of IoT sensors for real-time monitoring further enhances its potential impact on agriculture.

2.4 Disease Detection in Crops Using Remote Sensing Images: This paper explores the use of deep convolutional neural networks (CNNs) to detect diseases in crops using remote sensing images. The authors combined image features with metadata and used a technique called "data augmentation" to enhance the image dataset. Their model achieved high accuracy with a fast response time but had limitations in handling real-world images due to data dependency and the challenge of generating realistic images for detection.

2.5 Revolutionizing Crop Disease Detection with Computational Deep Learning: A Comprehensive Review, the research paper on revolutionizing crop disease detection with deep learning, focusing on the use of convolutional neural networks (CNNs) and vision transformers for accurate identification. The paper outlines the objective, technology, methodology, efficiency, and issues associated with this approach. The research aims to develop accurate and early disease detection methods, using extensive datasets and advanced models. While the model achieves high accuracy, limitations like limited data, similar disease symptoms, and environmental variability pose challenges, highlighting the need for further research and development.

III. STATUS OF AGRI VISION SYSTEM USING CNN FOR SMART FARMING

In modern agriculture, early detection of plant diseases is crucial for minimizing crop losses and ensuring food security. Traditional manual inspection methods are time-consuming and prone to errors, especially over large agricultural areas. To address this challenge, our proposed methodology employs automated techniques for plant disease detection, focusing on efficiency and accuracy. The National Status, To develop an automated, precise, and efficient system for detecting crop diseases and pests using deep learning, with the goal of improving crop productivity and reducing the time and effort required for manual inspection in large-scale farming. Deep Learning: Specifically, In modern agriculture, early detection of plant diseases is crucial for minimizing crop losses and ensuring food security. Traditional manual inspection methods are time-consuming and prone to errors, especially over large agricultural areas. To address this challenge, our proposed methodology employs automated techniques for plant disease detection, focusing on efficiency and accuracy. The National Status, To develop an automated, precise, and efficient system for detecting crop diseases and pests using deep learning, with the goal of improving crop productivity and reducing the time and effort required for manual inspection in large-scale farming. Deep Learning: Specifically,

- Fasal: **Model/Technology**: Fasal uses IoT-based devices and AI models, including **Convolutional Neural Networks (CNNs)**, to monitor crops and detect diseases through environmental data and crop images. The Key Features are, it Provides predictive analytics to farmers for disease management and crop advisory services.
- AgNext: **Model/Technology**: AgNext employs image-based deep learning models for identifying crop diseases, coupled with AI-powered drones for large-scale monitoring. The **Key Features** are, it focuses on quality analysis and disease detection, particularly in cash crops.

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- CropIn: **Model/Technology**: CropIn uses **decision-tree algorithms** and predictive analytics for early detection of diseases through satellite imagery and farm-level data. The Key Features are, it Provides a comprehensive farm monitoring system, integrating disease predictions with farm operations.

International Projects

- Bayer (Germany) **Model/Technology**: Bayer uses **AI-driven platforms** such as **Climate FieldView** to collect and analyze field data. Advanced **neural networks** are applied for crop disease diagnosis. The Key Features are, it Offers integrated pest and disease management systems with global applicability.
- Corteva Agriscience (USA) **Model/Technology**: Corteva employs **Vision Transformers (ViT)** for high-accuracy image-based disease detection. The Key Features are, it Integrates AI models into precision agriculture tools, focusing on disease prevention and control.
- Syngenta (Switzerland) **Model/Technology**: Syngenta incorporates **Capsule Networks (CapsNet)** into its digital tools for distinguishing between similar diseases like early and late blight. The Key Features are, it focuses on disease-specific solutions and recommendations.

IV. THE IMPLEMENTATION OF AGRI VISION SYSTEM USING CNN FOR SMART FARMING

1. **User Interface (UI) Module** of Early Detection of Crop Disease, purpose: Provides a web interface for users to upload images for disease prediction. The Implementation using HTML Template (index.html): Contains an upload form for users to select and submit an image file. Displays the uploaded image, the prediction result, and the confidence level after processing. Flask Route (/): Renders the homepage on a GET request. Processes the uploaded image and displays results on a POST request.

2. **File Upload and Validation Module** The Purpose of the Module is to, handle file uploads securely and validate that only images with allowed extensions are processed. Implementation: Validation: Checks if a file is present in the request (if 'file' not in request.files). Ensures that the uploaded file has an allowed extension (allowed_file(filename) function). File Handling: Saves the uploaded file securely using secure_filename. Stores the file in a predefined directory (static/) for further processing.

3. I**mage Preprocessing Module** Purpose: Prepares the uploaded image for prediction by resizing it to the model's input dimensions. Implementation: Image Loading: Loads the image using tf.keras.preprocessing.image.load_img. Resizing: Resizes the image to match the required dimensions (target_size=(IMAGE_SIZE, IMAGE_SIZE)). Image Array Conversion: Converts the image to an array using tf.keras.preprocessing.image.img_to_array and adds a batch dimension using tf.expand_dims.

4. **Prediction Module** Purpose: Uses the pre-trained deep learning model to classify the disease in the uploaded image. Implementation: Prediction Logic: The model. Predict() method processes the pre-processed image. Output Mapping: Maps the model's output to the respective class names (class names) using np.argmax to find the index of the predicted class. Computes the confidence score as a percentage of the model's highest prediction probability (np.max(predictions[0])).

5. **Result Display Module of Early Detection of Crop Disease** Purpose: Presents the prediction results (disease name and confidence level) alongside the uploaded image to the user. Implementation: Uses Flask's render_template method to dynamically render results on the homepage. Displays: The uploaded image (image_path). The predicted disease class (predicted_label).

6**. Backend Model Loading Module of Early Detection of Crop Disease** Purpose: Loads the trained TensorFlow model (model.h5) for inference. Implementation: Model loaded at the start of the application (tf.keras.models.load_model). Ensures the model is available globally to serve predictions efficiently without reloading.

7. **Debugging and Development Module** Purpose: Enables debugging and testing during the development phase. Implementation: The Flask application runs in debug mode (app.run(debug=True)), which provides detailed error logs and automatically reloads the server on code changes.

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V. METHODOLOGY OF AGRI VISION SYSTEM USING CNN FOR SMART FARMING

The proposed approach utilizes images to detect diseased plants. The key components include **Image Preprocessing**: Resizing images to 256x256 pixels, manual verification of labels, and data augmentation to improve model generalization and prevent overfitting**. Feature Extraction and Classification:** Utilizing a CNN-based architecture with transfer learning for feature extraction. Fine-tuning the model involves replacing specific layers to adapt the model to the crop disease and pest dataset, followed by classification using a softmax layer. The methodology ensures reliable detection of early-stage diseases, allowing farmers to take timely action. The system processes images captured from airborne platforms, such as drones, providing coverage for large agricultural fields.

5.1 Dataset used Early Detection of Crop Disease: The dataset used in this study is a collection of high-quality images of crop leaves, categorized into three main classes: **healthy**, **late blight**, and **early blight**. The images were obtained from two primary sources, **PlantVillage Repository**: A widely-used open-source dataset containing annotated images of various crop diseases. **Other Publicly Available Datasets**: Additional datasets were incorporated to improve diversity and ensure the model could generalize well across different environments and conditions.

5. 2. Preprocessing: The images underwent several preprocessing steps to prepare them for use in the model, **Enhancing Image Quality**: Techniques like contrast adjustment and noise reduction were applied to improve the clarity of the images, ensuring disease features like discoloration and patterns are visible. **Resizing**: All images were resized to a uniform dimension (e.g., 255x255 pixels) to meet the input size requirements of the CNN model.

5. 3. Model Architecture of Early Detection of Crop Disease: The study employs a **Convolutional Neural Network (CNN)**, a deep learning architecture designed for image recognition tasks. CNNs are particularly effective in detecting and analyzing visual patterns, such as disease symptoms on leaves. The model comprises several key components:
Convolutional Layers: Extract essential features like leaf texture, color changes, and disease patterns. These layers use filters to scan images for spatial features, capturing information about edges, spots, or regions affected by diseases. **Pooling Layers**: Reduce the size of feature maps produced by convolutional layers, which helps in downsampling the data while retaining key features. **Max Pooling** is typically used to select the most prominent feature values, which minimizes computational complexity and prevents overfitting. **Fully Connected Layers**: After the convolutional and pooling layers, the extracted features are flattened into a single vector.

VI. TRAINING AND VALIDATION OF EARLY DETECTION OF CROP DISEASE SYSTEM

6.1 The training process aims to optimize the CNN model to correctly classify crop diseases. Key aspects of the training methodology include: **Optimizer**: **Stochastic Gradient Descent (SGD)** is used to minimize the model's loss function by updating weights iteratively based on small batches of data. **Loss Function**: The **categorical cross-entropy loss function** measures how well the predicted probabilities match the actual classes. This loss is minimized during training to improve model accuracy. **Data Augmentation**: Techniques such as **rotation**, **flipping**, and **zooming** were applied to artificially expand the dataset. This step introduces variability in the training data, helping the model learn to recognize diseases under different orientations, scales, and lighting conditions.

6.2 Evaluation Metrics To assess the performance of the trained model, several metrics were used. These metrics provide insights into how accurately and effectively the model classifies each disease class: **Accuracy**: The proportion of correctly classified images out of the total number of images. Provides an overall measure of the model's performance. **Precision**: Measures how many of the images the model predicted as a specific disease class were actually correct. High precision indicates fewer false positives. **Recall**: Indicates how many of the actual diseased images the model successfully identified. High recall suggests the model is good at detecting diseases and has fewer false negatives.

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VII. CNN FOR EARLY DETECTION OF CROP DISEASE MODEL BUILDING AND DEPLOYMENT

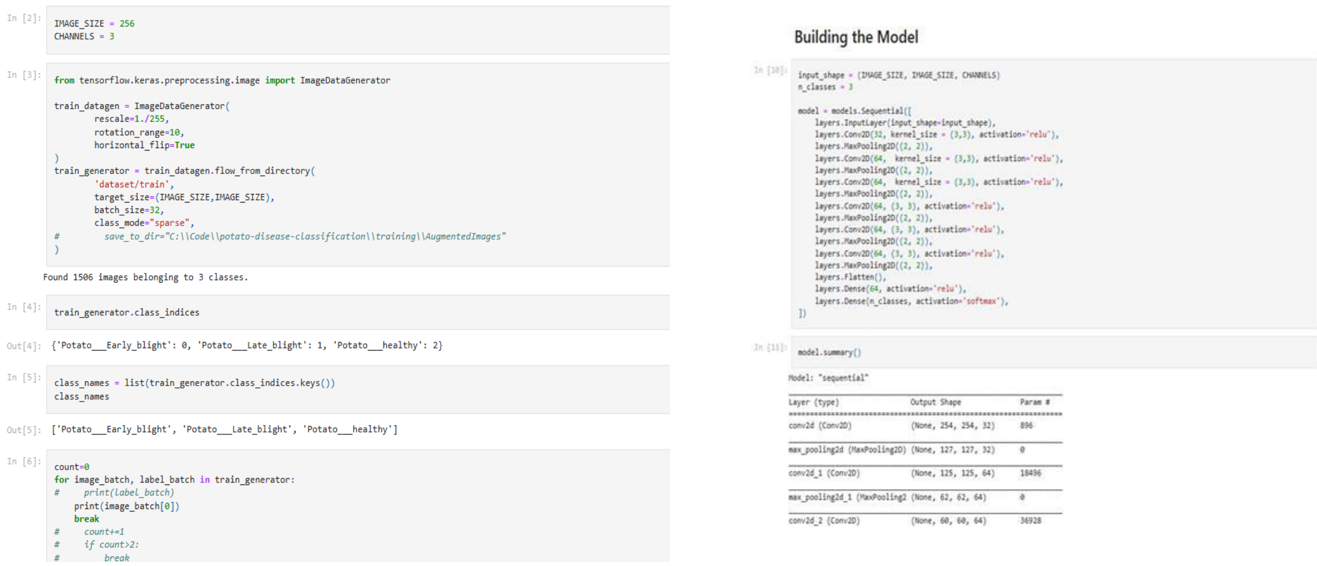
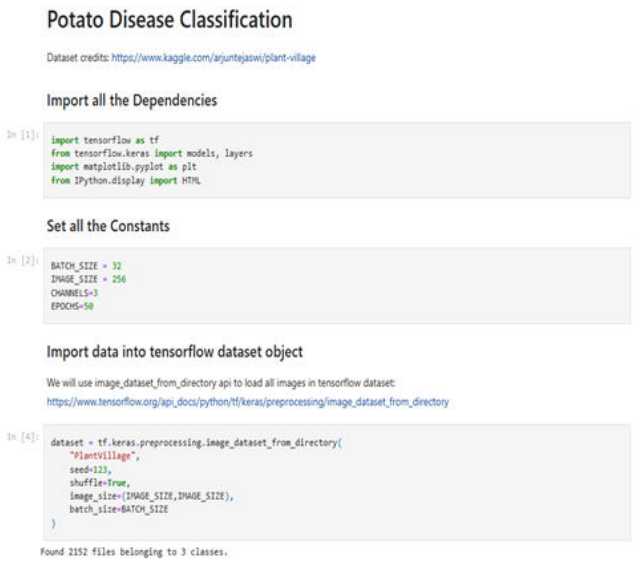


Figure 1: AgriVision System for Crop Care using CNN for Smart Farming Model Building



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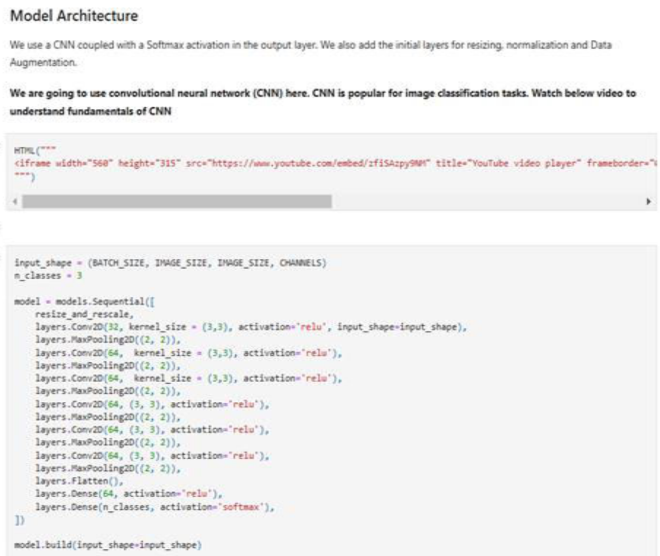
Model Architecture

We use a CNN coupled with a Softmax activation in the output layer. We also add the initial layers for resizing, normalization and Data Augmentation.

We are going to use convolutional neural network (CNN) here. CNN is popular for image classification tasks. Watch below video to understand fundamentals of CNN

```
HTML("""
<iframe width="560" height="315" src="https://www.youtube.com/embed/zfiSAzpy9NM" title="YouTube video player" frameborder="
""")
```

```
input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
n_classes = 3

model = models.Sequential([
    resize_and_rescale,
    layers.Conv2D(32, kernel_size = (3,3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),
])

model.build(input_shape=input_shape)
```

Figure 2: Agri Vision System for Crop Care using CNN to Detect Crop Disease Detection Model Deployment

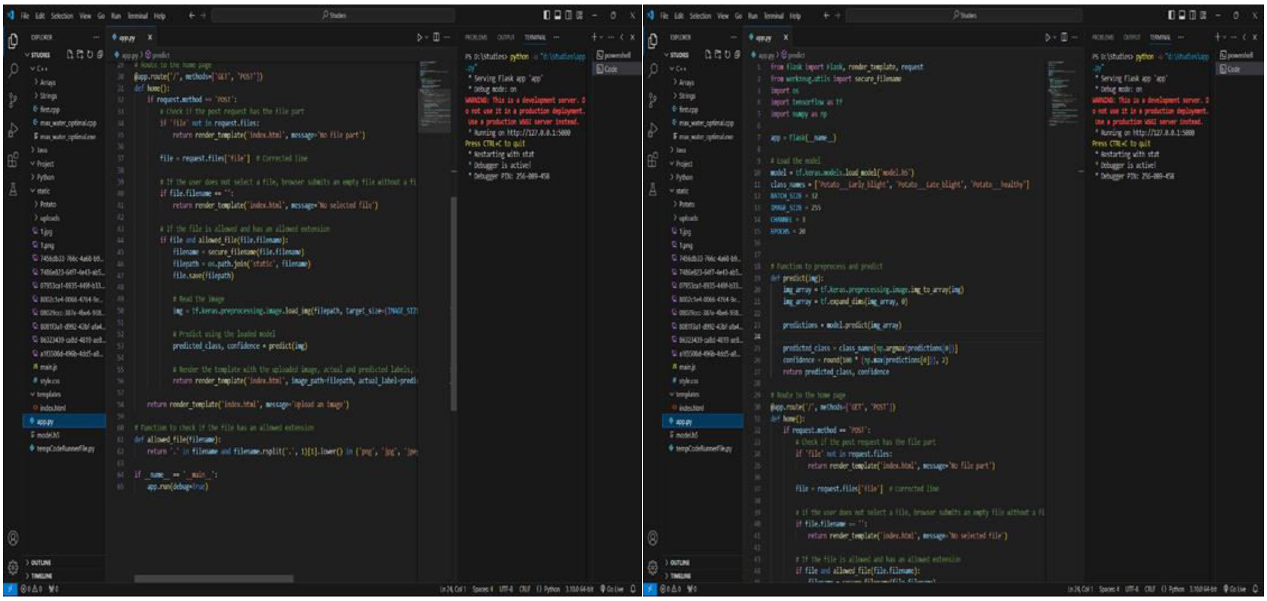

Figure 3: Agri Vision System: Flask and TensorFlow Files Used for Classification

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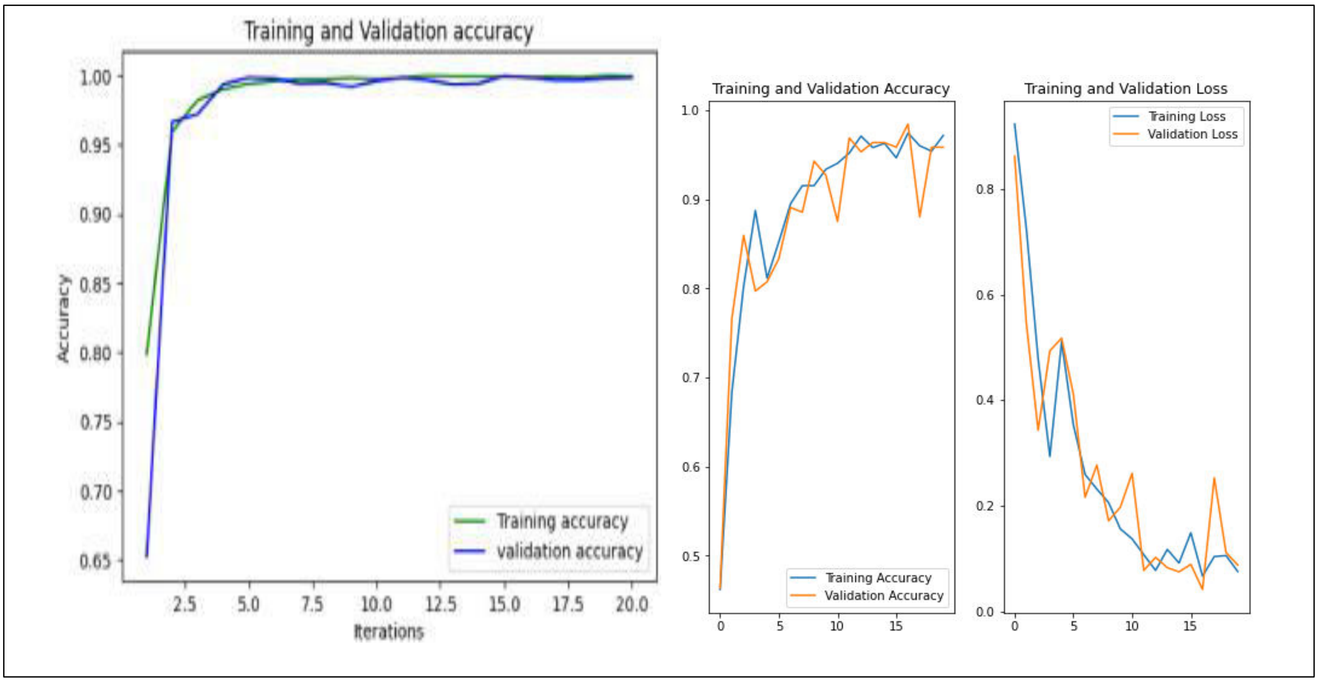

Figure 4: Accuracy Graph of AgriVision System: Early Detection of Crop Diseases for Smart Farming

VIII. EARLY DETECTION OF CROP DISEASE RESULT ANALYSIS AND SCREENSHOTS

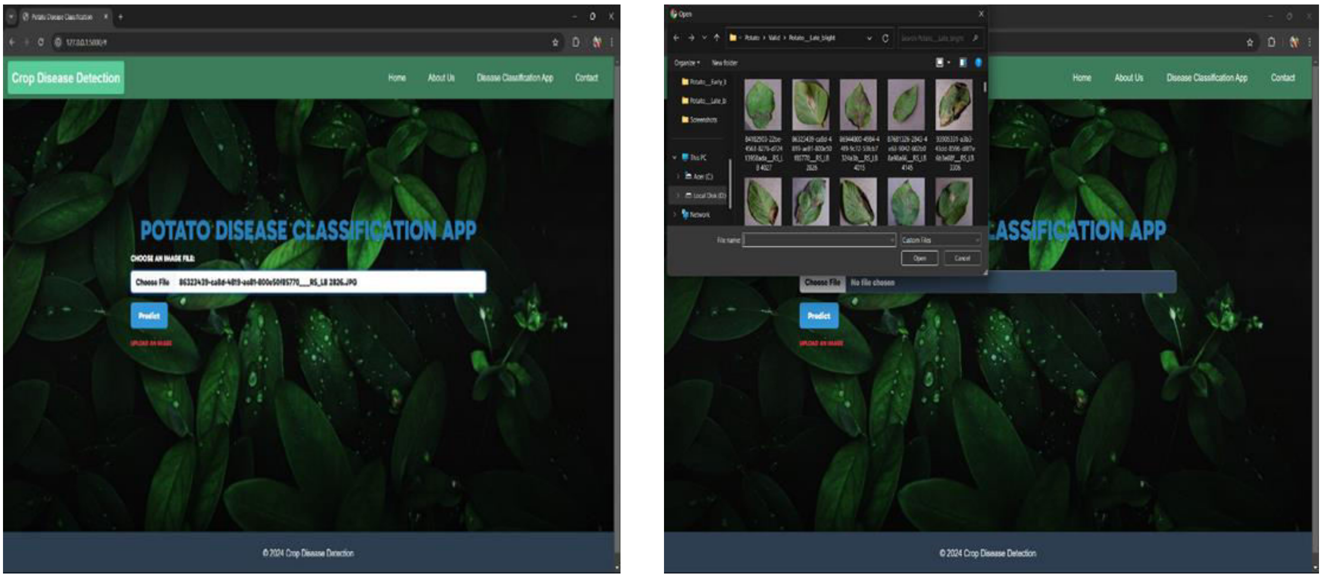

Figure 5: Potato Disease Classification using AgriVision System: Early Detection of Crop Diseases

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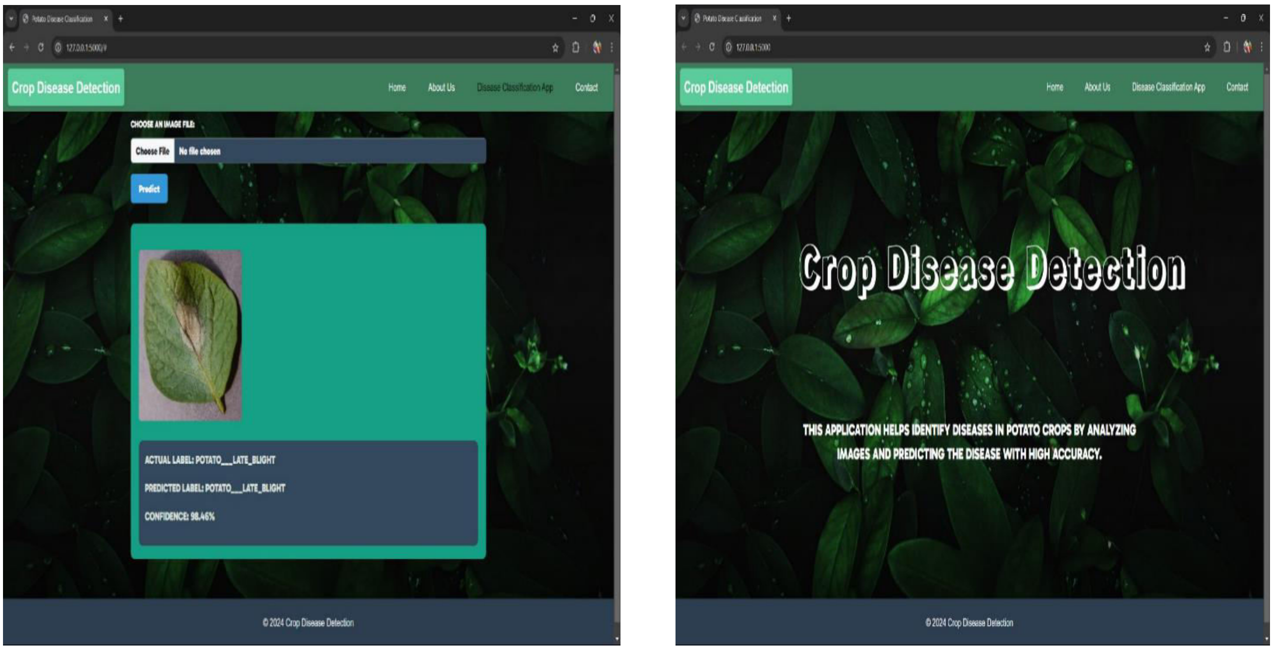

Figure 6: Result Analysis of AgriVision System: Early Detection of Crop Diseases for Smart Farming

IX. CONTRIBUTION AND FINDINGS EARLY DETECTION OF CROP DISEASE

The proposed AgriVision System: Early Detection of Crop Diseases for Smart Farming implementation using airborne images demonstrates promising results in early-stage disease detection. However, to expand the scope and applicability, the following enhancements are proposed, Development of a **Unified Framework**: Integrate multiple deep learning and machine learning algorithms to address diverse crop diseases effectively. **Focus on Leaf Images:** The majority of existing studies focus on leaf-based disease detection, though pests and diseases can affect other plant parts, potentially limiting the scope of current models. The methodology ensures reliable detection of early-stage diseases, allowing farmers to take timely action. The system processes images captured from airborne platforms, such as drones, providing coverage for large agricultural fields. **Many datasets** lack enough high-quality images of different crops and diseases, which makes it hard for models to learn accurately. These advancements will further enhance the scalability and efficiency of the system, making it suitable for monitoring extensive agricultural landscapes. **The AgriVision System** for Early Detection of Crop Diseases for Smart Farming model performed robustly on unseen data, ensuring reliability, while the disease-specific treatment recommendations added practical value for agricultural applications. The system showed potential for real-world impact by reducing crop loss and improving productivity, and its modular design allows for easy updates and future enhancements, such as incorporating new diseases or expanding to other plant species.

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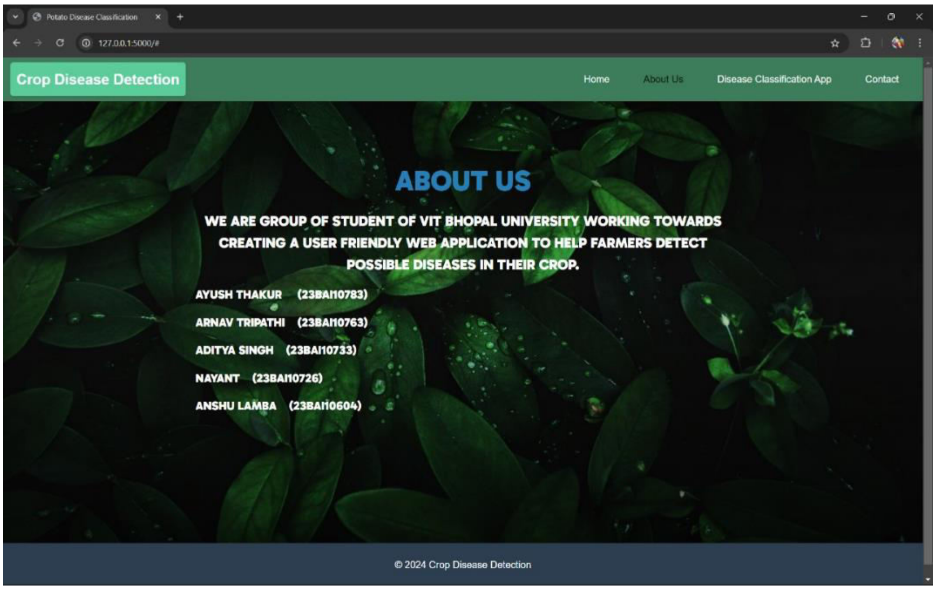

Figure 7: Disease Classification and Early Detection of Crop Disease Helpdesk

X. CONCLUSION

This research shows how powerful **Convolutional Neural Networks (CNNs)** can be for identifying crop diseases. It tackles a big challenge in farming by offering a reliable way to detect diseases early. With accurate disease classification, farmers can take quick action to prevent the spread of diseases, which helps reduce crop losses and boost productivity. By combining deep learning technology with farming, this approach opens the door to smarter, more efficient farming methods. It highlights how modern technology can make agriculture easier and more productive, benefiting both farmers and the global food supply. The proposed plant **disease monitoring** system is an efficient and accurate solution for automatic disease detection using image processing techniques. By enabling early disease detection, improving accuracy, and facilitating timely interventions, these advancements contribute to enhanced crop protection and food security. Traditional manual inspection methods are time-consuming and prone to errors, especially over large agricultural areas.

To address this challenge, our **proposed methodology** employs automated techniques for plant disease detection, focusing on efficiency and accuracy. The National Status, To develop an automated, precise, and efficient system for detecting crop diseases and pests using deep learning, with the goal of improving crop productivity and reducing the time and effort required for manual inspection in large-scale farming. This **innovative solution** paves the way for more sustainable and productive farming. This paper provides an innovative methodology for monitoring crop health through an automated and precise plant disease detection system. The approach leverages advanced image processing techniques, including Image Processing and deep learning, to identify diseased plants at an early stage. The primary aim is to enhance agricultural productivity by enabling timely interventions.

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