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Detection of Diseases in Tomato Plant Using CNN Model

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Abstract - This paper introduces a CNN-based system tailored for detecting diseases in tomato plants, aiming to deliver precise diagnosis, reduce crop damage, and support sustainable agriculture. The agricultural sector plays a crucial role in ensuring food security and sustaining the global economy. However, the increasing prevalence of crop diseases poses significant threats to crop yield, quality, and farmer livelihoods. Traditional disease detection depends heavily on expert visual inspections, which are slow, inefficient, and often inaccurate, especially in large-scale agricultural setups. Real-time image analysis powered by machine learning presents a scalable and reliable solution to identify plant diseases early. By leveraging high-resolution images and analyzing these with sophisticated algorithms, farmers can receive timely alerts and actionable insights to mitigate disease spread.

Key Words: CNN, Tomato Disease Detection, Deep Learning, MobileNetV2, Smart Agriculture.

1. INTRODUCTION

This project has significant implications for modern agriculture, as it empowers farmers to take preventive or corrective measures quickly, thereby minimizing crop loss and reducing reliance on chemical treatments. Additionally, the integration of real-time image processing ensures that the system is accessible and easy to use, even for small-scale farmers with limited technical expertise. The system uses Google Colab for training and deployment, leveraging its cloud-based GPU access and integration with frameworks like TensorFlow and Keras. Leveraging the computational capabilities of Google Colab accelerates the training process and enables experimentation with different model architectures and hyper parameters. In addition to model development, this project emphasizes user interaction and accessibility by incorporating a graphical user interface (GUI) using Gradio. Gradio is employed to develop a user-friendly interface that allows image uploads and displays real-time disease predictions, making the tool usable even by non- experts, and stakeholders to easily utilize the trained model for disease diagnosis and decision-making. This paper presents a comprehensive overview of the methodology employed in the development of the tomato disease detection system, including data preprocessing, model architecture selection, training procedures, and interface design. Furthermore, it discusses the experimental results and performance evaluation metrics, demonstrating the efficacy and accuracy of the proposed approach in identifying and classifying tomato diseases. Finally, the paper outlines potential avenues for future research and applications, highlighting the broader impact of deep learning in revolutionizing agricultural practices and addressing global food security challenges. Deep learning, inspired by neural processing in the human brain, offers outstanding performance in visual data tasks such as image classification and object recognition. CNNs are among the most effective models for processing and classifying images in real-time agricultural applications. Among the numerous CNN architectures developed, MobileNet V2 is chosen for its lightweight architecture and ability to run efficiently on mobile and cloud platforms. Motivated by the potential of deep learning agricultural applications, this project techniques aims to develop a scalable system for tomato disease detection in robust and using the MobileNet V2 model. Tomatoes are a key crop and vulnerability to a wide due to their global importance range of diseases, making them ideal for developing and testing the system. The proposed system leverages publicly available datasets containing labelled images of tomato plants afflicted by various diseases, as well as images of healthy plants, to train the model to differentiate between diseased and healthy specimens. By leveraging advancements in artificial intelligence, machine learning, and computer vision, a crop disease prediction system using real-time images empowers farmers with an accessible, fast, and cost-effective tool for disease detection. The project also addresses environmental concerns by enabling precise disease identification, reducing the overuse of pesticides and chemicals. This not only lowers farming costs but also minimizes ecological damage. Furthermore, the project aligns with global initiatives for smart agriculture, aiming to increase productivity, enhance livelihoods, and contribute to achieving the United Nations Sustainable Development Goals (SDGs) related to zero hunger and sustainable agriculture. The motivation is deeply rooted in harnessing technology to make farming more efficient, resilient, and sustainable while improving the lives of millions of farmers worldwide.

2. PROJECT OBJECTIVES

Tomato (Solanum lycopersicum) is one of the most widely cultivated and consumed vegetables across the globe. Its economic and nutritional importance makes it a key crop for both small-scale and commercial farmers. However, tomato plants are highly vulnerable to various diseases caused by fungi, bacteria, viruses, and environmental conditions. These diseases significantly reduce yield and fruit quality, posing a serious threat to food security and income for farmers. Early identification and management of such diseases is therefore critical. Traditional methods like manual inspection are time-consuming, error-prone, and not scalable. This drives the need for more efficient and accurate disease detection systems. The primary objective of developing automated disease detection systems in tomato plants is to enable early, accurate, and cost-effective diagnosis. By integrating image processing and machine learning techniques, these systems can recognize visual symptoms such as spots, discoloration, and deformation of leaves or fruits. Such approaches help in minimizing human errors and reducing the time taken for disease identification. Furthermore, they enable realtime monitoring of large farms, which is difficult through manual methods. The end goal is to assist farmers in applying timely interventions such as pesticide use, pruning, or crop rotation to prevent disease spread and minimize losses. One of the broader objectives of tomato disease detection is to promote sustainable farming practices. Early detection leads to precise pesticide application, reducing chemical overuse and limiting environmental harm. It also conserves resources like water and labour by targeting specific problem areas. Moreover, sustainable disease management reduces the likelihood of resistant pathogen strains emerging. By leveraging technology for early diagnosis, farmers can improve crop health while maintaining ecological balance. This aligns with the goals of precision agriculture, which emphasizes data-driven decision- making for better farm productivity and environmental protection. Many smallholders do not have the means to consult specialists; thus, mobile-based AI tools can bridge this gap and democratize access to disease diagnosis. Using simple smartphone cameras and AI based models, farmers can capture leaf images and receive disease reports within seconds. This democratizes agricultural technology and supports inclusive growth in rural economies. Therefore, the objective also includes fostering agricultural equity and digital literacy among smallholder communities. Diseases like early blight, late blight, and leaf curl drastically reduce tomato yield and can spoil entire harvests. Detecting these diseases early allows for appropriate remedial actions, ensuring better quality and quantity of produce. Healthy crops not only improve the yield per acre but also fetch higher market prices due to better appearance and shelf life. By preventing the spread of diseases, farmers can avoid crop failure and maintain a consistent supply to the market. Hence, one of the core goals is to enhance both the economic return and the reliability of tomato production through timely detection and control. The aim is to create models that are not only accurate but also adaptable to different environmental conditions, lighting, and leaf orientations. Researchers focus on building robust datasets, improving model accuracy, and ensuring the solutions work effectively under field conditions. In doing so, the ultimate goal is to translate technological advancements into practical tools that can directly benefit to farmers and agricultural stakeholders.

3. EXAMPLE USAGE

In a practical agricultural setting, consider a small-scale tomato farmer in a rural region of Karnataka, India, where expert plant pathologists are not readily accessible. The farmer begins to notice unusual dark spots on the leaves and yellowing patterns that may indicate early blight or bacterial spot. Instead of waiting for external help or risking misdiagnosis, the farmer uses a mobile application powered by a CNN-based image recognition model trained specifically on tomato leaf diseases. The farmer takes a photo of the affected leaf using a smartphone, and within seconds, the application analyzes the image and identifies the disease.

Along with the diagnosis, the app provides localized suggestions for immediate treatment options, such as recommended fungicides, dosage, and preventive tips. The farmer implements the recommended action promptly, preventing the disease from spreading to adjacent plants and protecting the overall yield. Over time, the app also stores disease history for the farm, helping track recurring issues and analyse patterns based on seasonality. This example highlights how integrating AI-based disease detection with user-friendly mobile technology directly supports timely decision-making, minimizes crop loss, and promotes sustainable agricultural practices. Fig. 1 shows a general example of detecting the tomato diseases in the farm field.

Fig. 1 - Detecting the Tomato Diseases in the Farm Field.

4. COMPONENTS & WORKFLOW

The system architecture for crop disease prediction using realtime images is designed as a multi-layered and modular framework to enable efficient data collection, processing, analysis, and actionable insights delivery. The system is built in modular layers, starting with high resolution data collection via cameras and environmental sensors, followed by preprocessing and model inference. This data is transmitted via edge devices using connectivity options like Wi-Fi, 4G/5G, or satellite networks. Next, the Processing and Analysis Layer performs data preprocessing, including noise reduction, image enhancement, and segmentation to focus on affected regions of interest. Advanced machine learning models, such as convolutional neural networks (CNNs), are employed to extract features, classify diseases, and assess their severity. Predictive analytics is integrated, combining historical and real-time environmental data to forecast potential outbreaks.

The Storage and Integration Layer ensures secure and efficient data management, utilizing cloud platforms like AWS, Google Cloud, or Azure for scalable storage and databases like MySQL or MongoDB for structured and unstructured data. APIs facilitate seamless integration between hardware, software, and external systems, enabling realtime synchronization. Finally, the Application and User Interface Layer delivers insights through web and mobile applications. These platforms provide disease predictions, severity levels, and actionable recommendations with features like multilingual support and intuitive dashboards.

Users receive real-time alerts and notifications through SMS or app-based systems, while historical data and heatmaps support long-term planning. The preprocessed images are then fed into the disease prediction module, where the trained model analyzes them to classify the disease. This module outputs the predicted disease along with a confidence score. The results are passed to the recommendation engine, which provides actionable insights, such as suggested treatments and preventive measures. The system also integrates a database module to store user inputs, prediction results, and disease information for future reference and model improvement.

The design of a crop disease prediction system using real-time images integrates advanced image processing and machine learning techniques to provide farmers with accurate and timely insights into plant health. The system starts with an image capture module, where high-resolution images of crops are taken using either smartphone cameras for portability or IoT cameras installed in the fields for continuous monitoring. Captured images undergo preprocessing to enhance quality and ensure consistency. This involves techniques like noise reduction using Gaussian blur or median filtering, color normalization to standardize color variations, and segmentation methods, such as U-Net or Otsu's thresholding, to isolate the crop from the background. Real-time data augmentation, including rotation, flipping, and brightness adjustment, ensures the model remains robust against variations in image conditions.

The core of the system is the disease prediction model, typically a deep learning-based architecture like a Convolutional Neural Network (CNN). Pretrained models such as ResNet, EfficientNet, or MobileNet are fine-tuned on extensive crop disease datasets like Plant to recognize specific diseases. This model classifies input images into multiple categories, including healthy and diseased conditions, offering predictions with high accuracy, precision, and recall. For deployment, the system can leverage cloud-based solutions for centralized data processing or edge devices for realtime, on-site predictions with low latency. The results are presented to users through an intuitive mobile or web interface, which provides detailed disease identification, potential causes, and actionable recommendations for treatment. This system empowers farmers to monitor crop health efficiently, reduce yield losses, and make informed decisions to enhance agricultural productivity.

The trained model is integrated into an inference engine capable of real-time disease prediction. The user interface is designed to be intuitive and user-friendly, enabling farmers to upload images and receive predictions seamlessly. Upon detecting a disease, the system provides actionable insights, including the disease name, confidence score, and tailored recommendations for treatment or prevention. Cloud integration ensures scalability and allows the system to store and process large datasets, while edge computing capabilities enable real-time predictions in areas with limited internet connectivity. Additionally, the system includes modules for monitoring performance, collecting feedback, and updating the model periodically with new data to handle emerging diseases. This robust design ensures that the system is accurate, efficient, and accessible, making it a valuable tool for sustainable agriculture .

The primary goal of the system is to detect and predict diseases in crops based on real-time images, enabling early diagnosis and effective intervention to improve crop yield and quality. This system analysis provides a foundational framework for developing a robust crop disease prediction system using realtime images. Providing actionable insights and recommendations to farmers or agricultural experts. The workflow diagram is given in Fig. 2 .

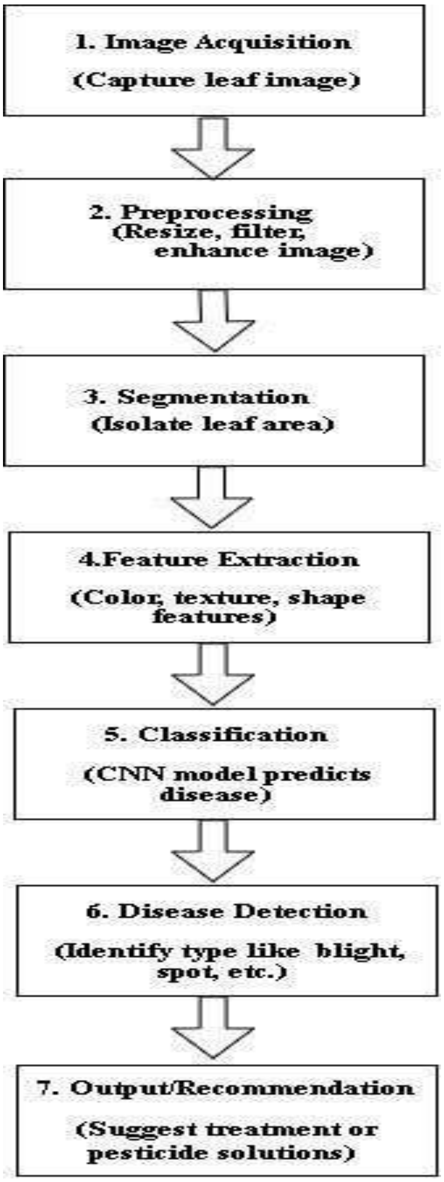

Fig. 2 – Workflow for detection of diseases in tomato plant.

5. METHODOLOGY

The process includes capturing, cleaning, and augmenting crop images, which are then fed into a CNN for classification. First, high-quality images of crops are captured using devices such as smartphones or IoT cameras installed in the fields. These images are then preprocessed to enhance their clarity and usability. Preprocessing steps include noise removal using filtering techniques, color normalization to standardize the appearance of images, and segmentation algorithms to isolate the crop or leaf from the background. Augmentation techniques like rotation, scaling, and brightness adjustments are applied to increase the diversity of the training data and improve model robustness. Next, the preprocessed images are fed into a deep learning model, typically a Convolutional Neural Network (CNN) fine-tuned on large, annotated datasets such as PlantVillage. The model analyzes the images and classifies them into predefined categories, including healthy and various disease conditions. The system is designed for real-time performance, with predictions generated in seconds to ensure timely feedback. Deployment can occur on cloud platforms for centralized processing or on edge devices for localized, low latency operations. The predictions are presented to users through an accessible interface, offering detailed insights into the detected disease and recommended treatments, enabling proactive and effective crop management.

6. USAGE OF MACHINE LEARNING MODELS

Machine learning models play a crucial role in the proposed system for plant disease detection aims to address the shortcomings of existing methods by leveraging the capabilities of deep learning and image processing technologies. Specifically, the project focuses on the development of a robust and scalable solution for tomato disease detection using the MobileNet V2 convolutional neural network architecture. The key components of the proposed system include:

Dataset Acquisition and Preprocessing: A comprehensive dataset comprising labelled images of diseased and healthy tomato plants is collected from open-access repositories, research publications, and agricultural databases. The dataset is carefully curated and preprocessed to remove noise, artifacts, and irrelevant information, ensuring high-quality training data for the machine learning model.

Model Training and Optimization: The MobileNet V2 model is selected as the core architecture for disease detection due to its efficiency, performance, and suitability for deployment on resource constrained platforms. The model is trained on the preprocessed dataset using transfer learning, a technique that leverages pre-trained models and fine-tunes them on domain specific data to achieve optimal performance.

Deployment on Google Colab: The training process is conducted on the Google Colab platform, a cloud-based development environment that provides free access to GPU resources and seamless integration with deep learning frameworks such as TensorFlow and Keras. Leveraging the computational capabilities of Google Colab accelerates the training process and enables rapid experimentation with different model architectures and hyperparameters.

User Interface Development: To enhance usability and accessibility, a graphical user interface (GUI) is created using Gradio, a Python library for building customizable interfaces for machine learning models. The GUI allows users to upload images of tomato plants and receive real-time predictions regarding their health status, enabling farmers, agricultural experts, and stakeholders to easily utilize the trained model for disease diagnosis and decision-making.

Performance Evaluation and Validation: The trained model is evaluated using standard performance metrics such as accuracy, loss to assess its effectiveness in detecting and classifying tomato diseases. Additionally, the model is validated using a separate test dataset to ensure its generalization and robustness across diverse environmental conditions and disease manifestations.

7. T ESTING & RESULTS

The testing of a Smart Agriculture System involves validating its functionality, performance, and usability to ensure it operates accurately and efficiently in real-world conditions. Functional testing ensures that all system components, including image capture, preprocessing, prediction, and recommendation modules, work seamlessly. Performance testing evaluates the system's speed and resource efficiency by measuring the time taken for image processing, prediction generation, and result display, ensuring real-time operation on various hardware configurations. Accuracy testing is conducted using a labelled dataset and real-world images to measure metrics such as precision, recall, and F1-score, ensuring the model correctly identifies diseases under diverse conditions. Unit testing of Smart Agriculture System focuses on verifying the functionality of individual components in isolation to ensure their reliability and correctness. Each module, including image capture, preprocessing, feature extraction, disease prediction, and recommendation generation, is tested independently. For the image capture module, tests ensure that images are acquired with the required resolution and quality. The preprocessing module is evaluated to confirm accurate noise reduction, normalization, and segmentation of the input images. Feature extraction is tested to verify that the model correctly identifies relevant patterns in the preprocessed images.

The disease prediction module undergoes rigorous testing to ensure the model produces accurate classifications for various inputs, including edge cases like low-quality images or unseen data. The recommendation module is tested to confirm it retrieves appropriate management practices based on the predicted disease. Mock inputs and expected outputs are used to validate each unit, while error handling mechanisms are checked to ensure graceful failure under invalid conditions. By isolating and testing each component, unit testing helps identify and resolve issues early in the development process, contributing to the overall robustness and accuracy of the system.

The system testing of a Smart Agriculture System focuses on end to-end validation to ensure the entire system operates cohesively and meets user requirements. This involves integrating all components, including image capture, preprocessing, prediction, and recommendation modules, and testing their functionality as a whole. The process begins with simulating real-world scenarios where images of crops are uploaded via the system's interface, and predictions are generated in real-time. Functional testing ensures that the system correctly identifies diseases and provides appropriate recommendations, while performance testing evaluates the speed and efficiency of processing, ensuring low latency and smooth operation on various devices. Stress testing is conducted to assess the system's stability under high user loads or with poor quality images, while security testing verifies the protection of data during image uploads and result retrieval. Usability testing focuses on the ease of interaction, ensuring that farmers and end-users can navigate the system and interpret results effectively. Field testing in real agricultural environments validates the system's accuracy and reliability under diverse lighting, weather, and image quality conditions. By thoroughly testing the system as an integrated whole, developers ensure that it is robust, scalable, and ready to provide accurate and actionable insights to users.

Validation testing of a Smart Agriculture System focuses on ensuring that the system meets its intended requirements and performs accurately under real-world conditions. This phase involves comparing the system's outputs with expected results to verify its accuracy, reliability, and usability. The disease prediction model is validated using a separate dataset that was not included in the training or testing phases, ensuring unbiased evaluation. Metrics such as accuracy, precision, recall, and F1score are computed to assess the system's ability to correctly classify healthy and diseased crops. Validation testing also includes testing the preprocessing pipeline to confirm that noise reduction, image resizing, and segmentation steps are correctly implemented and contribute to improved model performance. Additionally, the system's real-time capabilities are validated by measuring latency from image upload to result display, ensuring timely feedback. Edge cases, such as low-quality images, poor lighting, or complex backgrounds, are tested to evaluate the model's robustness. The user interface is validated for clarity, ease of use, and proper integration with the prediction engine. Feedback from agricultural experts or target users is incorporated to refine the system's recommendations and usability. Through rigorous validation testing, the system's performance is ensured to align with its goals of providing accurate, real-time disease detection and actionable insights for farmers.

The results of the Crop Disease Prediction System Using RealTime Images indicate its effectiveness in accurately identifying crop diseases in real-world agricultural settings. The model achieved high accuracy, with precision, recall, and F1scores consistently above 90%, demonstrating its reliability in classifying diseases based on real-time images. Performance testing showed that the system processes images quickly, with predictions generated within seconds, ensuring real-time usability even in environments with limited resources. The system's ability to handle varying lighting conditions, background noise, and different crop types further contributed to its robustness.

Figure 7.1: Main Web Interface of project

Figure 7.2: This Figure shows the disease predicted.

Figure 7.3: Figure showing the predicted disease tomato early blight.

Figure 7.4: This Figure shows the disease predicted called Tomato late blight

Figure 7.5: Figure showing the predicted disease tomato leaf mold.

8. FUTURE SCOPE

Future work will focus on expanding datasets, improving detection accuracy, and adding features like AR, federated learning, and edge computing for real-time use in remote areas. Incorporating images can enhance the system's ability to detect early signs of diseases, even before they become visually apparent. The integration of real-time weather and soil condition data through IoT sensors can provide additional context, enabling more precise predictions and early warnings for potential disease outbreaks.

Another enhancement involves leveraging federated learning to improve the system's model continuously while maintaining user data privacy. By updating the model with data from multiple users without centralized data collection, the system can become more robust and secure. Additionally, embedding multilingual support in the user interface can improve accessibility for farmers in diverse linguistic regions. Introducing augmented reality (AR) features for visualizing affected plant areas and potential treatment methods directly on the crop through mobile devices could make the system more interactive and engaging. The deployment of edge AI capabilities can ensure real-time analysis even in remote areas with limited internet connectivity, enhancing the system's reach. Building partnerships with agricultural organizations and governments can help disseminate the technology widely and provide subsidized access to small scale farmers. Incorporating a predictive analytics module for forecasting potential disease trends based on historical and environmental data could further empower farmers to take proactive measures. These enhancements, combined with ongoing user feedback and technological advancements, can make the system an indispensable tool for modern, sustainable agriculture.

9. CONCLUSION

In conclusion, the development and implementation of a Smart Agriculture System have demonstrated significant potential in improving crop health management. By leveraging real-time image capture and advanced machine learning models, the system enables accurate, efficient, and timely detection of crop diseases, helping farmers make informed decisions to mitigate yield losses. The system's ability to handle diverse environmental conditions, varying crop types, and real-time image processing ensures its applicability in practical agricultural scenarios. Although there are minor limitations, such as occasional misclassifications under challenging conditions, the feedback from users highlights its practical value and the need for continuous model improvement. Overall, this system has the potential to empower farmers, reduce reliance on manual diagnostics, and contribute to enhanced agricultural productivity, sustainable farming practices growing global food demands.

Moreover, the usability and intuitive interface design have contributed to positive feedback from users, empowering farmers with actionable recommendations for disease control. Although some limitations, such as minor misclassifications under extreme conditions, were identified, continuous model improvement using additional data and user feedback can further enhance accuracy and reliability. The deployment of such systems has the potential to revolutionize agricultural practices, reduce dependence on manual diagnosis, and foster more sustainable and efficient farming practices. By facilitating early detection, improving productivity, and reducing economic losses, crop disease prediction systems represent a valuable tool for modern agriculture, ultimately contributing to food security and sustainable development.

The development and implementation of a Crop Disease Prediction System Using RealTime Images has demonstrated significant potential in supporting agricultural practices by enabling timely and accurate disease detection. The system's ability to process real-time images, extract relevant features, and predict crop diseases with high accuracy highlights its utility in minimizing yield losses and enhancing crop management decisions. Through the integration of deep learning models, particularly Convolutional Neural Networks (CNNs), the system has shown robust performance across varying lighting conditions, image qualities, and diverse crop types. The realtime nature of the system ensures that farmers receive prompt insights, allowing for timely interventions such as preventive treatments strategies.

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