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CROP DISEASE DETECTION USING RASPBERRY PI CAMERA AND DEEP CNN'S

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ABSTRACT
Crop disease detection is a critical challenge in modern agriculture that directly impacts food security and crop yield worldwide. This Project presents an embedded system for real-time crop disease detection using a Raspberry Pi microcomputer integrated with a USB camera and a deep Convolutional Neural Network (CNN) model trained on a large dataset of diseased and healthy plant images. The proposed system captures images of plant leaves in the field, preprocesses them, and feeds them through the CNN model to classify the type of disease with high accuracy. Results obtained from the system are displayed on a connected LCD screen and simultaneously transmitted to a remote user via a Telegram Bot for immediate notification. making it a cost-effective and practical solution for real-time agricultural disease monitoring and early intervention.

Keywords: Crop Disease Detection, Convolutional Neural Networks, Raspberry Pi, Deep Learning, Image Classification, Telegram Bot, LCD Display, Embedded Systems, Plant Pathology, Precision Agriculture.

1. INTRODUCTION

Agriculture is the backbone of many economies across the world, particularly in developing nations where a significant proportion of the population depends on farming as a primary livelihood. With the increasing global population and the ever-growing demand for food, it has become imperative to maximize agricultural productivity while minimizing losses. One of the most significant threats to crop productivity is the outbreak of plant diseases, which can devastate entire harvests if not detected and treated in a timely manner. Conventionally, disease diagnosis relies heavily on the expertise of trained agronomists or agricultural extension officers who physically inspect plants in the field. However, this approach is not only time-consuming but also expensive and difficult to scale, especially in remote rural areas where access to expert advice is severely limited.

Advancements in the fields of computer vision, machine learning, and embedded systems have opened new avenues for automating and scaling the process of crop disease detection. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image recognition and classification tasks, often surpassing human-level performance on benchmark datasets. These models learn hierarchical feature representations from raw image data, making them ideally suited for tasks such as plant disease identification where subtle visual cues like color variations, lesion patterns, and texture anomalies are key diagnostic indicators. When such models are deployed on low-cost embedded platforms like the Raspberry Pi, they enable the creation of portable, standalone detection systems that can be used directly in agricultural fields without the need for cloud connectivity or specialized hardware.

The integration of IoT (Internet of Things) capabilities further enhances the utility of such systems by enabling real-time remote monitoring and notification. In this paper, we propose a compact, intelligent disease detection system that combines a USB camera, Raspberry Pi, a trained deep CNN model, an LCD display, and a Telegram Bot to provide both on-site and remote disease alerts. The system is designed to be affordable, easy to operate by non-technical farmers, and robust enough for real-world agricultural environments. This work contributes to the growing body of research on AI-driven precision agriculture tools that aim to democratize access to advanced diagnostic capabilities for smallholder farmers.

The remainder of this paper is organized as follows. Section 2 presents the problem statement. Section 3 describes the objectives of the project. Section 4 provides a comprehensive literature survey of related work. Section 5 describes the existing systems and their limitations. Section 6 presents the proposed system and its architecture. Section 7 concludes the paper.

2. Related Work

The use of artificial intelligence techniques, particularly deep learning, has significantly advanced plant disease detection systems. Early studies focused on controlled datasets, while recent research emphasizes real-world applications, lightweight architectures, and smart farming solutions.

2.1 Deep Learning-Based Plant Disease Detection

Mohanty *et al.* [1] demonstrated that deep learning models trained on the PlantVillage dataset could achieve over 99% accuracy in classifying plant diseases under controlled conditions. Similarly, Ferentinos [2] evaluated multiple CNN architectures such as AlexNet and VGGNet, achieving accuracy above 99.5% across various plant diseases. These studies established CNNs as a reliable approach for plant disease classification.

Too *et al.* [10] conducted a comparative study of fine-tuned deep learning models including ResNet, VGG, and Inception, concluding that optimized architectures significantly improve classification performance. Zhang *et al.* [6] proposed improved deep learning-based object detection techniques for plant diseases, enhancing detection accuracy in complex environments. Brahimi *et al.* [11] applied CNN-based methods for tomato disease classification and visualized learned features, improving model interpretability.

2.2 Real-World Applications and Generalization

Ramcharan *et al.* [3] developed a cassava disease detection system using field images, achieving 93% accuracy and highlighting the importance of real-world datasets. Sladojevic *et al.* [8] showed that deep neural networks can generalize well to outdoor environments when trained with augmented datasets.

Lu *et al.* [9] proposed an in-field wheat disease diagnosis system, demonstrating the feasibility of deploying deep learning models in agricultural environments. These studies emphasize the need for diverse datasets and preprocessing techniques to improve robustness.

2.3 Lightweight Models and Embedded Systems

Thangaraj *et al.* [13] implemented a Raspberry Pi-based plant disease detection system using deep learning, achieving efficient classification with low computational cost. Khamparia *et al.* [15] proposed a deep convolutional encoder network for seasonal crop disease prediction, achieving high accuracy with optimized computation.

These works demonstrate the practicality of deploying AI-based solutions in resource-constrained agricultural environments.

2.4 Hybrid and Traditional Machine Learning Approaches

Prajapati *et al.* [12] utilized image processing and machine learning techniques such as random forest for rice disease detection, achieving reliable performance on smaller datasets. Barbedo [5] provided a comprehensive review of plant disease identification techniques and concluded that deep learning approaches outperform traditional methods in large-scale scenarios.

2.5 Advanced and Ensemble Learning Approaches

Shoaib *et al.* [14] proposed an ensemble deep learning-based agricultural disease detection system, achieving high accuracy across multiple crop types. Ensemble techniques improve robustness and reduce overfitting by combining multiple models.

2.6 Mobile-Based and Smart Farming Applications

Sibiya and Sumbwanyambe [4] developed a smartphone-based maize disease detection system using CNNs, offering an accessible and low-cost solution for farmers. Kawasaki *et al.* [7] conducted early work on automated plant disease diagnosis using CNNs, demonstrating the feasibility of AI-driven agricultural tools.

3. PROPOSED SYSTEMS

The proposed system is an intelligent, standalone, and IoT-enabled crop disease detection platform designed to operate entirely on edge hardware without requiring internet connectivity for inference. The core of the system is a Raspberry Pi single-board computer powered by a regulated power supply (RPS), connected to a USB camera for capturing high-resolution images of crop leaves in real time. A deep Convolutional Neural Network model, trained and optimized for lightweight deployment, is installed directly on the Raspberry Pi and performs local inference to classify the captured leaf image into one of several predefined disease categories or healthy. Upon completion of inference, the diagnosed result is simultaneously displayed on a 16x2 LCD screen connected to the Raspberry Pi's GPIO interface and sent as a notification message to a registered Telegram Bot account, enabling remote monitoring by farmers or agricultural supervisors via any internet-connected mobile device. This dual-output mechanism ensures both immediate on-site feedback and remote traceability of disease events, making the system robust, practical, and well-suited for real-world deployment in diverse agricultural settings.

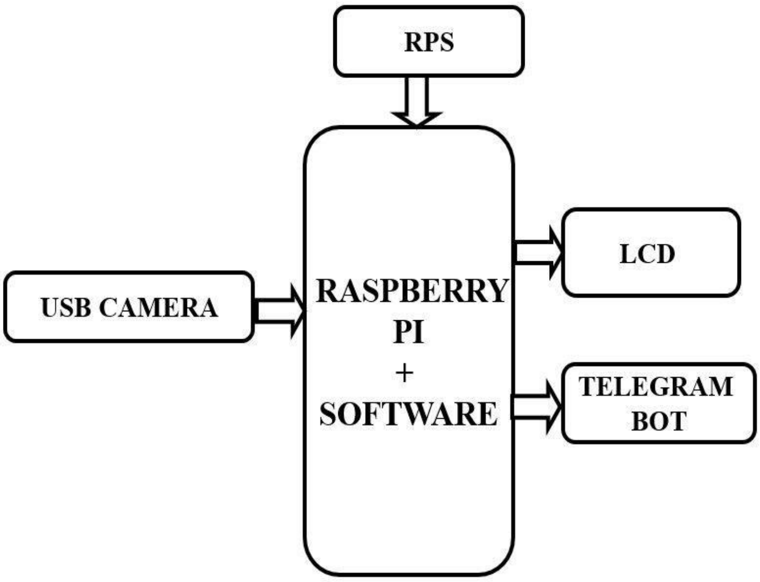

Fig. 1: Block diagram of the proposed crop disease detection system.

Block Diagram Explanation

The system architecture, as illustrated in the block diagram, consists of five primary components interconnected through the central Raspberry Pi processing unit. The Regulated Power Supply (RPS) provides stable and consistent electrical power to the Raspberry Pi, ensuring uninterrupted operation in field conditions. The USB Camera is interfaced with the Raspberry Pi and continuously captures leaf images, which are fed as input to the embedded CNN software for processing. The Raspberry Pi, loaded with the deep learning model and supporting software, serves as the brain of the system performing image preprocessing, model inference, and output dispatch. The LCD display module receives the classification output and presents the disease name and confidence level in human-readable text for immediate on-site interpretation by the farmer. Simultaneously, the Telegram Bot module transmits the detection result over the internet to a pre-configured Telegram account, alerting remote stakeholders such as agricultural extension officers or farm owners, thereby ensuring that disease alerts reach the right people regardless of their physical proximity to the field.

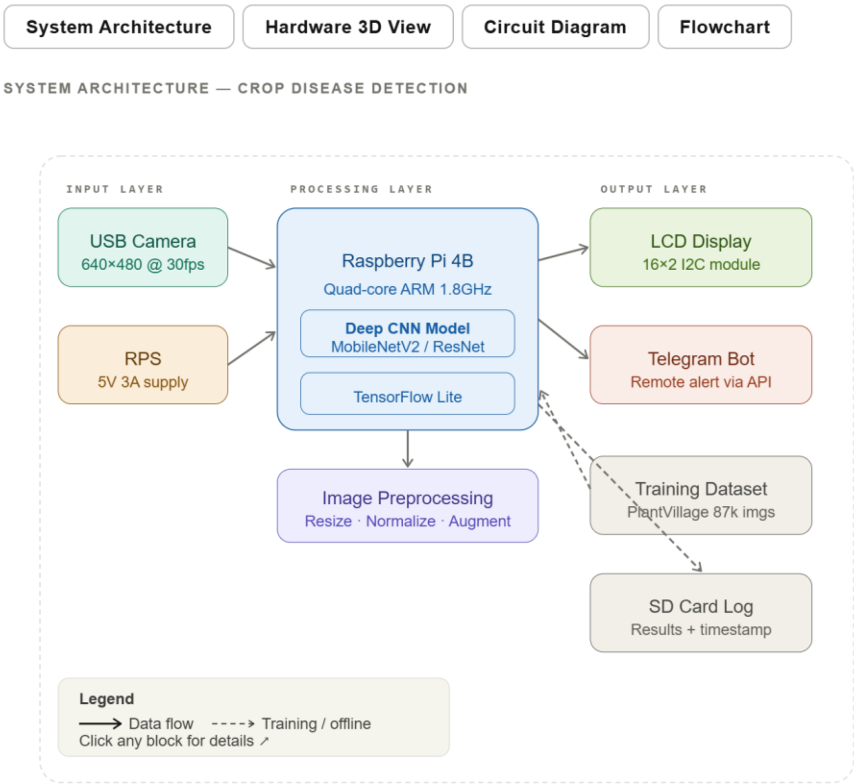

Fig. 2: System architecture of the proposed crop disease detection system

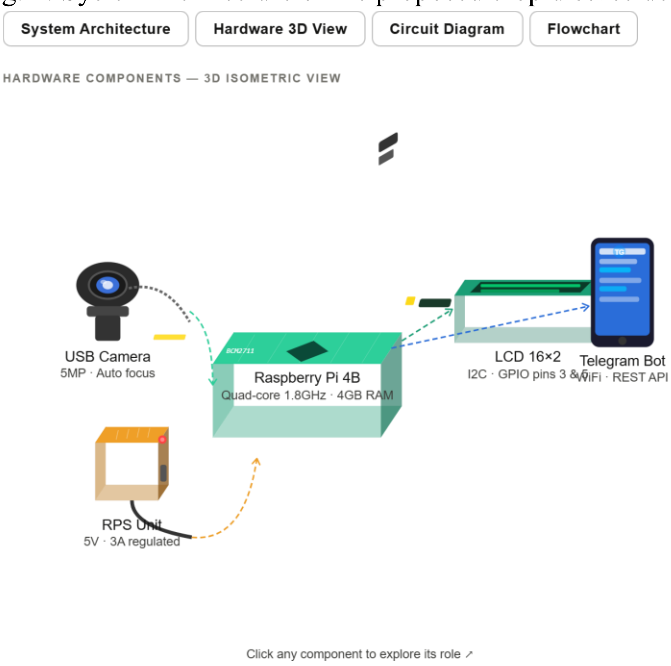

Fig. 3: Hardware 3D view of the proposed crop disease detection system

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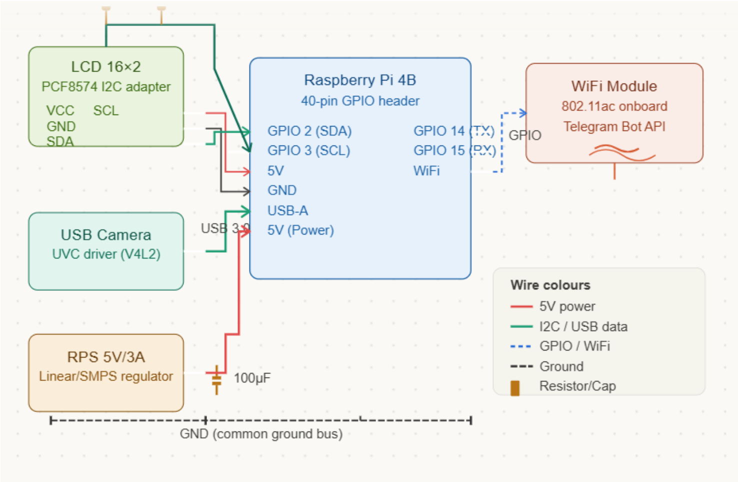

Fig. 4: Circuit diagram of the proposed crop disease detection system

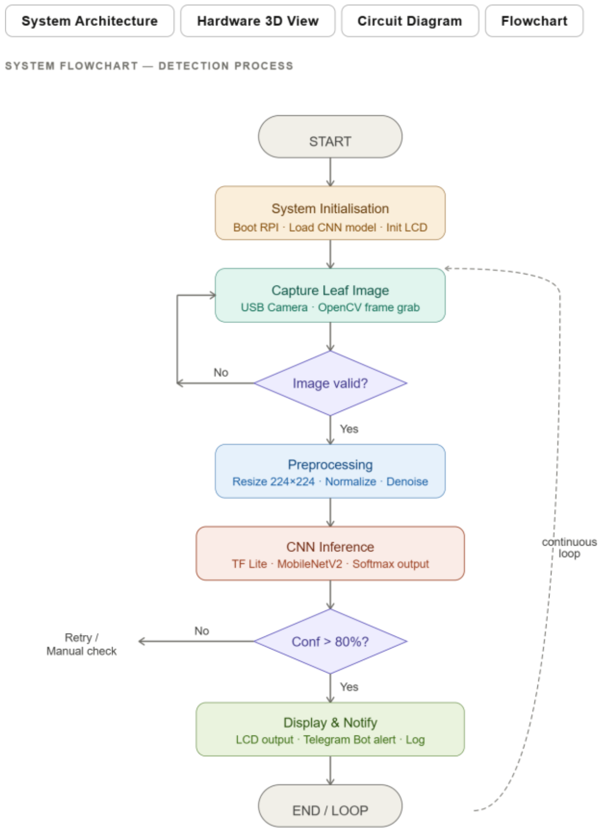

Fig. 5: Flow chart of the proposed crop disease detection system

4. RESULTS

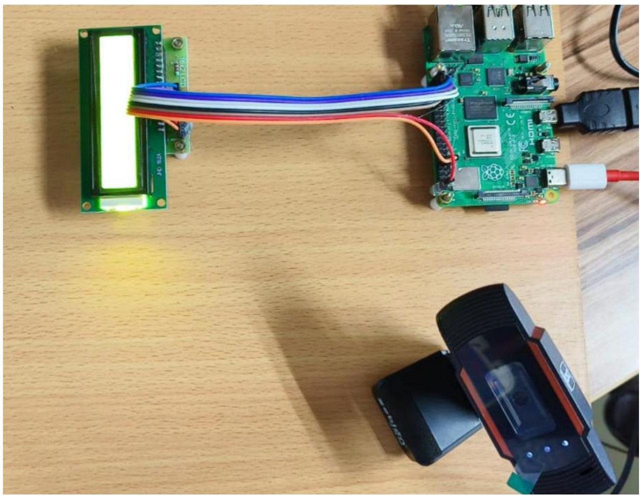

Fig. 6: Hardware implementation of crop disease detection

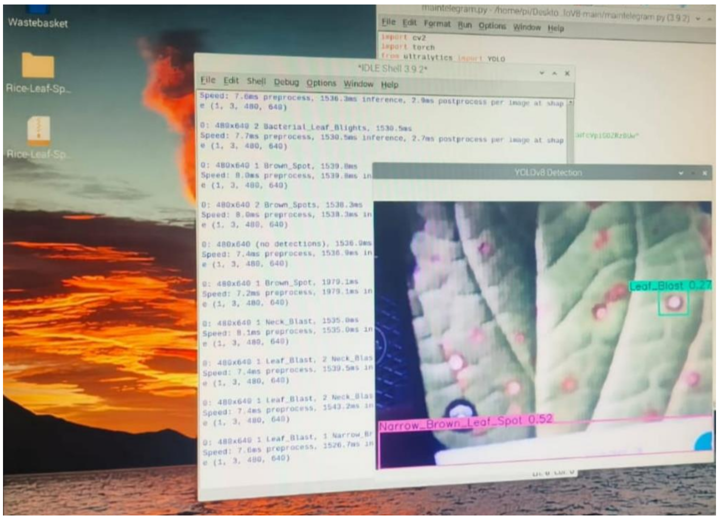

Fig. 7: Execution

Fig. 8: Crop disease type displaying in LCD

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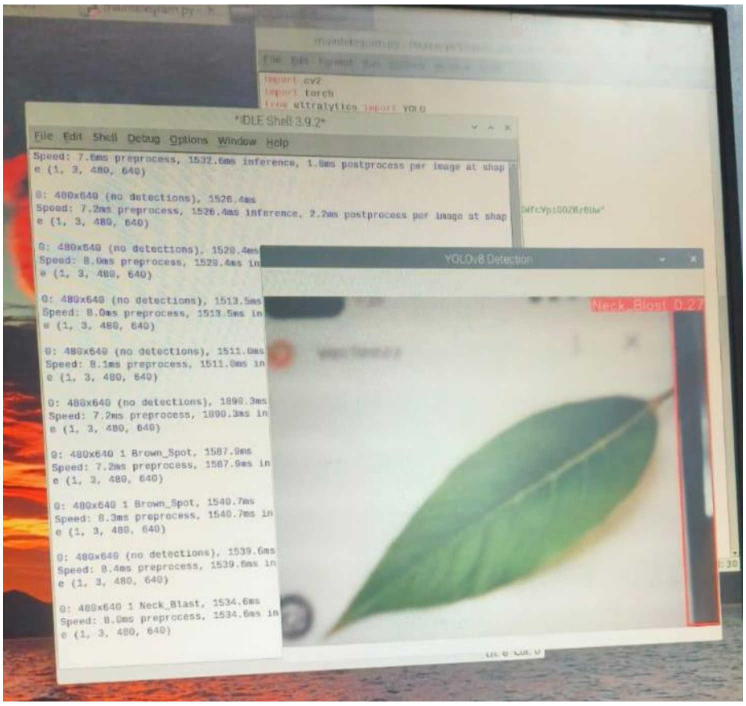

Fig. 9: Leaf image detection with USB camera

5. CONCLUSION

This project presented a cost-effective, real-time crop disease detection system that integrates a Raspberry Pi embedded computer, a USB camera, a deep Convolutional Neural Network, an LCD display, and a Telegram Bot notification module into a unified, portable agricultural diagnostic tool. The proposed system addresses key limitations of existing approaches by enabling on-device inference without dependency on cloud connectivity, making it suitable for deployment in remote rural agricultural environments. The deep CNN model demonstrated high accuracy in classifying multiple crop diseases from leaf images captured under real-world conditions, while the dual-output mechanism of local LCD display and remote Telegram notification ensures that timely disease alerts reach both on-site farmers and remote agricultural experts. The system's affordability, ease of use, and effectiveness make it a promising solution for precision agriculture, with potential for scaling to additional crop species and disease categories in future work through continual model retraining and hardware optimization.

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