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Ensemble-Based Plant Disease Detection with Mini TensorFlow on RISC Devices and Chatbot

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Abstract - This study focuses on training and testing various convolutional neural network (CNN) models, including Basic CNN, AlexNet, VGG16, and EfficientNet B0, for efficient plant disease detection. Each model was evaluated using the New Plant Diseases Dataset from Kaggle, covering a variety of plant species and diseases, to analyze performance, accuracy, and efficiency. The trained models were then integrated into a Marathi language chatbot to enable real-time disease identification and provide agricultural guidance. This research offers insights into the strengths and limitations of different models for precision agriculture, particularly in applications that support regional languages to promote accessible, sustainable farming practices.

***Key Words*:** Precision Agriculture, Embedded Systems, IoT, Deep Learning, Model Comparison, Real-time Detection, Disease Classification, NLP, Chatbot Integration, Marathi Chatbot.

1.INTRODUCTION

The rapid advancement of precision agriculture, fueled by technological innovations, has reshaped crop management and underscored the need for effective tools in plant disease detection to support sustainable food production. Machine learning, particularly convolutional neural networks (CNNs), has epoch-making in this field, delivering improved accuracy and efficiency [1]. As agriculture moves further into the digital age, integrating intelligent systems on edge devices is essential, enabling real-time monitoring and decision-making directly in the field. Additionally, bridging language barriers through tools like a Marathi-language chatbot becomes crucial [1], providing accessible information to diverse linguistic communities and enhancing farmers' ability to respond quickly to disease-related issues. This study evaluates four CNN architectures—Basic CNN, VGG16, EfficientNet B0, and AlexNet—deployed on the Raspberry Pi 5, a versatile edge computing device, to analyze their accuracy and efficiency under real-world constraints. Furthermore, the integration of a Marathi chatbot offers a user-friendly interface for farmers, providing disease detection insights in their native language. The study uses the New Plant Diseases Dataset [4] to ensure a realistic and representative basis for training and evaluation. In addition to accuracy, this research examines response time latency, which is critical for timely interventions. The web application supports model accessibility and real time testing, with the Marathi chatbot serving as a direct resource for local farmers [1]. This research aims to guide practitioners and researchers in selecting CNN models that deliver accuracy, efficiency, and accessibility in the evolving landscape of precision agriculture.

2. PROBLEM STATEMENT

Plant diseases pose a significant threat to agricultural productivity, leading to economic losses and food insecurity. Traditional detection methods are labor-intensive and often inaccurate. This project aims to develop an ensemble-based plant disease detection system optimized for RISC devices, using lightweight deep learning models for efficient, real-time analysis. Additionally, a Marathi-language chatbot will provide farmers with instant disease diagnosis and management advice, making the solution accessible and effective in resource constrained environments.

3. OBJECTIVES

1. Literature Review: Analyze and compare existing literature on CNN-based methods for identifying plant diseases in real-time [4].

2. Embedded System Proposal: Propose a solution for plant disease detection based on an embedded system, emphasizing the utilization of Raspberry Pi 5. The proposal should prioritize cost-effectiveness and suitability for deployment in resource constrained agricultural environment.

3. Data Collection and Continuous Improvement: The scope involves the systematic collection and curation of a diverse dataset over an extended period. This dataset captures various plant diseases and environmental conditions, serving as a foundation for continuous model refinement and enhancement.

4. Ensemble-Based Deep Learning: Enhance the performance of the proposed solution by systematically evaluating and incorporating ensemble-based deep learning techniques [5]. This includes a critical examination of existing algorithms and the exploration of new approaches to improve accuracy and robustness in disease detection.2

5. Marathi Chatbot Integration: Implement a Marathi-language chatbot as part of the proposed solution, serving as an intuitive interface for farmers. The chatbot should enable users to upload crop images, receive real-time disease diagnosis, and access relevant agricultural advice.

6. User-Centric Approach: Adopt a user-centric approach by actively soliciting and incorporating user feedback. This will inform system improvements, enhancing the utility and user experience for the farming community.

7. Ensure the system's scalability, security, and reliability to meet the diverse needs of farmers and stakeholders in the agriculture sector.

8. Interdisciplinary Collaboration: Encourage collaboration between experts in agriculture, computer science, and data collection methodologies. Interdisciplinary efforts will provide a holistic perspective, addressing the unique challenges of plant disease detection in real-world farming scenarios.

4. RELATED WORK

Model selection is a crucial aspect of building a successful plant disease detection system [1]. It is essential to choose deep learning models that can accurately identify diseases while also being efficient enough to run on resource-constrained devices like the Raspberry Pi. After extensive testing, four models were selected based on their accuracy and efficiency [1]: Basic CNN, AlexNet, VGG16, and EfficientNet B0. Each of these models offers unique strengths that contribute to the overall robustness of the system.

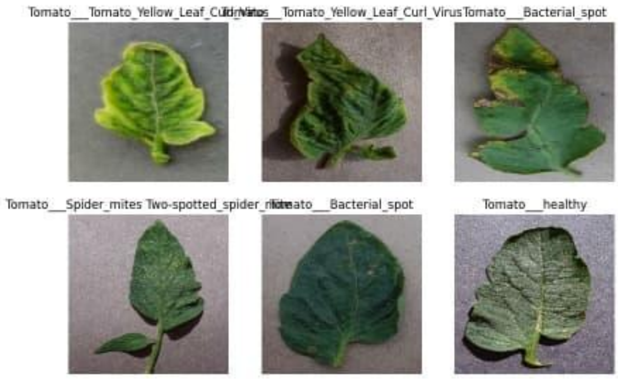

Fig.1 Tomato Images Dataset

The basic Convolutional Neural Network (CNN) serves as a foundational model for the project, achieving an impressive accuracy rate of over 90%. This model's simplicity and effectiveness in classification tasks provide a reliable baseline, showcasing the project's capacity to achieve high accuracy without excessive complexity. The Basic CNN is a relatively lightweight model, making it suitable for edge computing environments and demonstrating that even fundamental architectures can yield strong results in plant disease detection.

As one of the pioneering architectures in deep learning, AlexNet has been successfully implemented with accuracy exceeding 90%. This model is included in the system for its historical significance and proven performance in image classification tasks. AlexNet's architecture, featuring deep layers and ReLU activation functions [2], provides the power needed for effective feature extraction in plant disease images. The model's performance highlights the diversity and strength of deep learning techniques employed in the project, reinforcing its role in building a reliable detection system. Known for its consistent, deep convolutional layers, VGG16 achieves an accuracy rate above 90%, making it a strong performer in high-accuracy image classification tasks. The architecture of VGG16, with 16 carefully structured layers, is advantageous for extracting complex features related to plant diseases. This model's deep structure provides a robust framework for accurate and reliable disease detection, ensuring that the system can handle intricate details in disease symptoms. VGG16's proven track record in classification tasks makes it a valuable addition to the model suite.

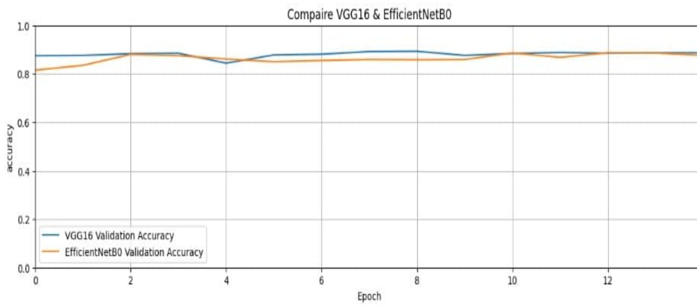

Fig.2 Accuracy of VGG16

EfficientNet B0 stands out for its ability to balance accuracy and resource efficiency, making it highly suitable for real-time applications on edge devices like the Raspberry Pi. Achieving an accuracy rate above 90%, EfficientNet B0 leverages innovative scaling techniques, allowing it to maintain high accuracy while using fewer resources. This efficiency is especially beneficial for deploying the model in practical agricultural settings where computational resources are limited. EfficientNet B0's streamlined architecture optimizes the system's performance without compromising on precision, ensuring timely and accurate disease detection.

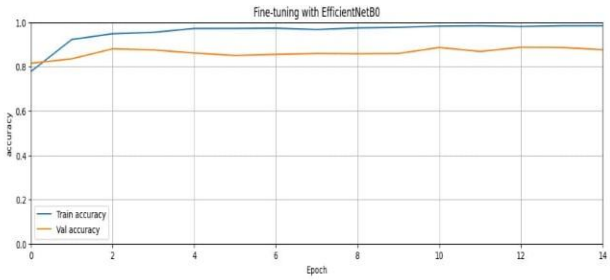

Fig.3 Accuracy of EfficientNet B0

Together, these four models Basic CNN, AlexNet, VGG16, and EfficientNet B0 form the backbone of the plant disease detection system. Each model is selected for its high accuracy and suitability for edge computing, contributing to a balanced and efficient approach to disease detection. By combining these architectures, the system aims to deliver reliable, real-time disease identification, supporting farmers in managing plant health effectively in the field.

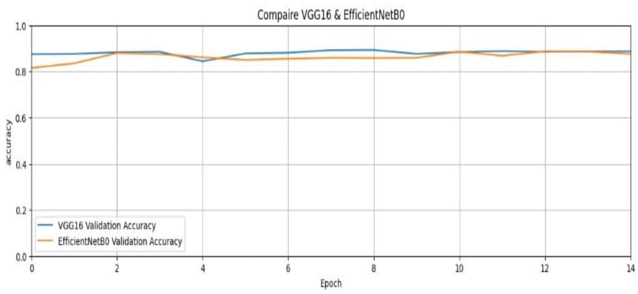

Fig.4 Comparison of VGG16 and EfficientNet B0

5. DRAWBACKS OF EXISTING SYSTEM

First, image quality [4] varies due to inconsistent lighting or conditions when farmers take photos, which can reduce detection accuracy. Improved image processing might help with this issue.

Second, ensemble models, while accurate, can be slow, causing delays in real-time detection when quick results are needed. Reducing latency [1] would make them more practical for field use.

Third, the models may not work well on all crops or rare diseases, meaning they need more diverse data and fine-tuning to improve generalizability.

Finally adapting the solution across different agricultural settings each with unique crops, climates, and languages requires significant adjustments to make it broadly usable.

6. PROPOSED ARCHITECTURE

The high-level system design presents a holistic view of our innovative solution for plant disease detection and interaction with farmers [3]. The system integrates advanced technologies and components to create a user-friendly and efficient platform [8]. The key components include an IoT device, deep learning models, cloud infrastructure, and a Marathi chatbot. The system's functional flow for plant disease detection involves capturing images using a Raspberry Pi-based IoT device, processing them with OpenCV, and employing an ensemble of deep learning models (EfficientNet, VGG16, custom CNN and AlexNet) for accurate disease detection. The system makes decisions based on model predictions and interacts with users through a Marathi-language chatbot for real-time disease diagnosis and recommendations. Data is securely communicated and visualized via a cloud-based web interface, supported by AWS infrastructure. The hardware setup, including the Raspberry Pi 5 and a high-quality camera module, is designed to be scalable and adaptable, enabling effective deployment in diverse agricultural environments.

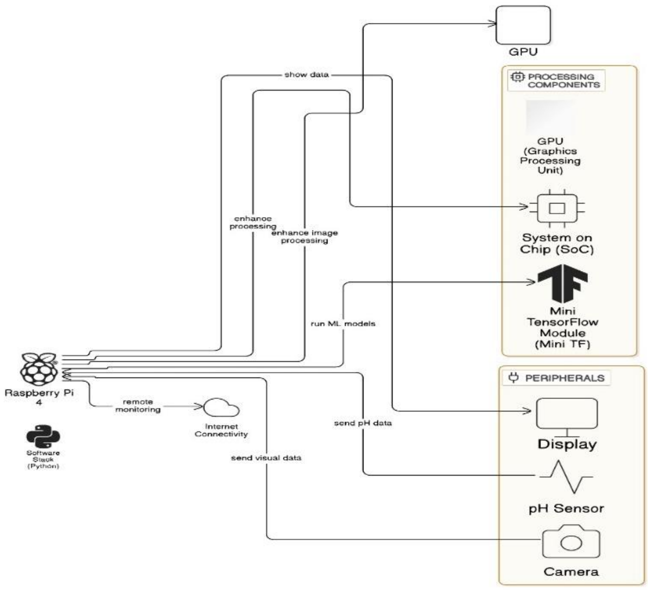

Fig.5 Plant Disease Detection Architecture

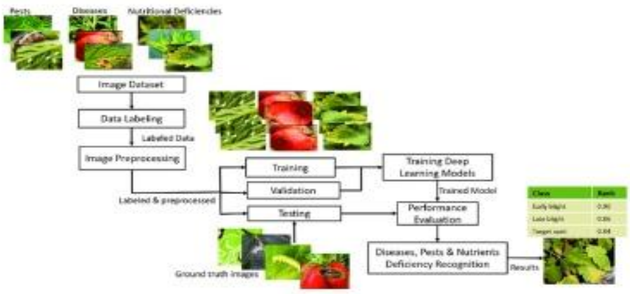

Fig.6 Deep Learning for Disease Detection

CONCLUSION

The project develops an ensemble-based plant disease detection system using lightweight deep learning models on Raspberry Pi 5, optimizing performance with MiniTensor-Flow for efficient real-time analysis. A comprehensive dataset enhances model accuracy, while a Marathi-language chatbot offers instant disease diagnosis [6] and management advice, improving accessibility for farmers. The system is designed to be scalable and user-friendly, ensuring usability and security resource constrained agricultural environments.

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