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Ensemble-Based Plant Disease Detection with Mini Tensor Flow on Risc Devices and Chatbot

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Abstract: The research trains and evaluates multiple CNN architectures, including Basic CNN, AlexNet, VGG16, and EfficientNet B0, to enhance the accuracy of plant disease identification. Each model was tested using the New Plant Diseases Dataset from Kaggle, which includes various plant species and diseases, in order to assess performance, accuracy, and efficiency.

The trained models were subsequently integrated into a Marathi language chatbot to facilitate real-time disease detection and provide agricultural guidance. This study provides valuable insights into the strengths and limitations of different models for precision agriculture, especially in applications that support regional languages to encourage accessible and sustainable farming practices. Additionally, a Marathi language chatbot is incorporated, enabling users to obtain plant disease information instantly through a user-friendly web application.

Keywords—Precision Agriculture, Embedded Systems, IoT, Deep Learning, Model Evaluation, Real-time Detection, Disease Identification, NLP, Chatbot Integration, Marathi Chatbot

I. INTRODUCTION

The rapid advancement of precision agriculture, supported by technological innovations, has transformed crop management and emphasized the need for effective plant disease detection tools to ensure sustainable food production. Machine learning, particularly convolutional neural networks (CNNs), has played a significant role in this field by greatly improving accuracy and efficiency. As agriculture continues to adopt digital technologies, the integration of intelligent systems on edge devices becomes increasingly important, enabling real-time monitoring and decision-making directly in the field. Furthermore, addressing language barriers through tools such as a Marathi-language chatbot is essential, allowing farmers from diverse linguistic backgrounds to quickly access important disease-related information

This study evaluates four CNN architectures—Basic CNN, VGG16, EfficientNet B0, and AlexNet—implemented on the Raspberry Pi 5, a powerful edge computing device, to analyze their performance in terms of accuracy and efficiency under real-world conditions. In addition, the integration of a Marathi chatbot provides an intuitive interface for farmers, delivering disease detection insights in their native language. The study uses the New Plant Diseases Dataset to establish a reliable and representative foundation for model training and evaluation

Beyond accuracy, this research also examines response time latency, which is a crucial factor for timely agricultural interventions. A web-based application ensures easy access to the models and supports real-time testing, while the Marathi chatbot serves as a direct assistance tool for local farmers. timely agricultural interventions. A web-based application ensures easy access to the models and supports real-time testing, while the Marathi chatbot serves as a direct assistance tool for local farmers.

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II. PROBLEM STATEMENT

Plant diseases present a major challenge to agricultural productivity, resulting in economic losses and food insecurity. Conventional detection techniques are often time-consuming, labor intensive, and prone to inaccuracies. This project focuses on developing an ensemble-based plant disease detection system optimized for RISC devices, leveraging lightweight deep learning models to enable efficient, real-time analysis. Additionally, a Marathi-language chatbot will offer farmers immediate disease diagnosis and management guidance, ensuring that the solution remains accessible and effective, even in resource-limited environments.

III. METHODOLOGY

The proposed system follows a systematic methodology for developing an efficient plant disease detection framework using deep learning, edge computing, and chatbot integration. Initially, the dataset was collected from the New Plant Diseases Dataset available on Kaggle, which contains images of healthy and diseased plant leaves from various crops such as tomato, potato, and corn. These images were then preprocessed through resizing, normalization, noise reduction, and augmentation techniques such as rotation, flipping, zooming, and brightness adjustment to improve model accuracy and reduce overfitting.

After preprocessing, four Convolutional Neural Network architectures—Basic CNN, AlexNet, VGG16, and EfficientNet B0—were trained and evaluated for plant disease classification. Each model was analyzed on the basis of classification accuracy, computational efficiency, and suitability for real-time implementation. To further enhance prediction performance, an ensemble learning approach based on soft voting was applied, where the outputs of multiple models were combined to generate a final prediction with higher reliability and robustness.

The optimized ensemble model was converted into TensorFlow Lite format for deployment on Raspberry Pi 5, a RISC-based edge computing device. Quantization and optimization techniques were used to reduce memory usage, model size, and inference time while maintaining high accuracy. A camera module connected to the device captures live leaf images, and the system performs disease prediction locally in real time without depending on cloud connectivity.

To improve accessibility for farmers, a Marathi-language chatbot was integrated into the web-based application. The chatbot provides disease identification results, treatment suggestions, preventive measures, and crop care guidance in the local language. The complete system was evaluated using performance metrics such as accuracy, precision, recall,

F1-score, latency, and inference speed to determine the most effective model for practical agricultural deployment. This methodology ensures a smart, scalable, and farmer-friendly solution for precision agriculture.

IV. 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 resourceconstrained de vices like the Raspberry Pi.

A. Graphical Representation

The Basic Convolutional Neural Network achieves an impressive accuracy rate of over 90%. This model's simplicity and effectiveness in classification

tasks provide areliable baseline, showcasing the project's capacity toachieve 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 frame work for accurate and reliable disease detection, ensuring that the system can handle intricate details in disease symptoms. VGG16's proventrack record in classification tasks makes it a valuable addition to the model suite

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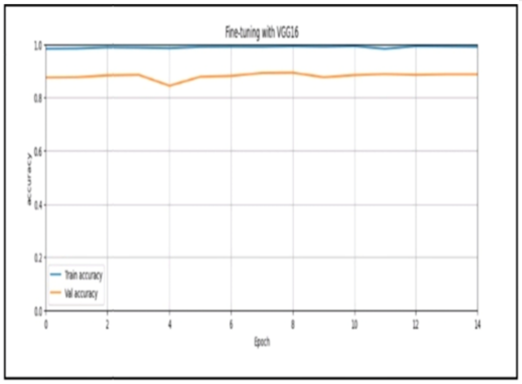
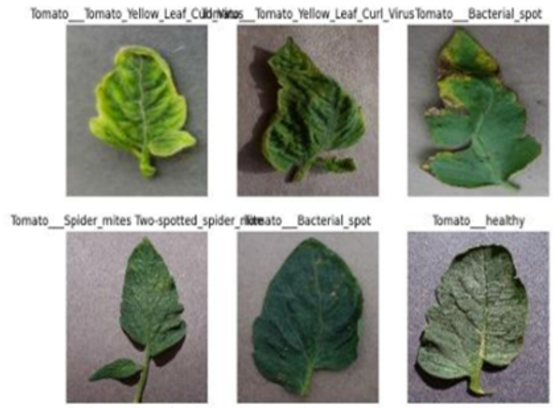


Fig.2. Accuracy of VGG16



.Fig 1: Tomato Image Dataset

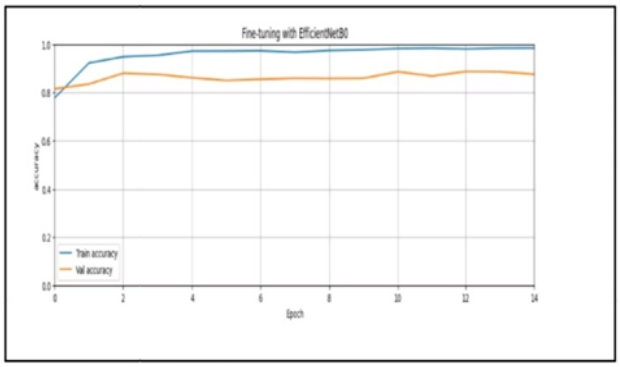


Fig.3. Accuracy of EfficientNet B0

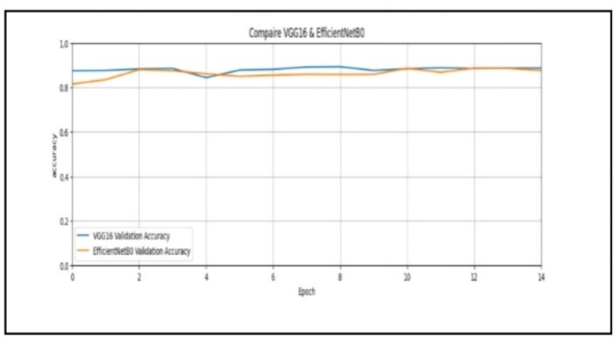


Fig.4. Comparison of VGG16 and EfficientNet B0

EfficientNet B0 stands out for its ability to balance accu racy and resource efficiency, making it highly suitable for realtime 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.

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.

B. Interface

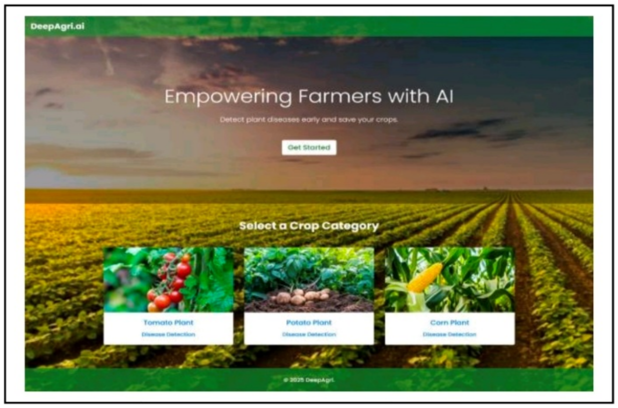


Fig.5. User Interface

The homepage features a welcoming interface with a large agricultural background, emphasizing AI-driven plant disease detection. It allows users to choose from three crop categories: Tomato Plant, Potato Plant, and Corn Plant. Each category directs users to disease detection options, ensuring targeted analysis for different crops.

The authors in [1] proposed a blockchain and edge computing solution for securing drug supply chains by using a decentralized method of recording supply chain operations. Their solution enhances the authenticity and verifiability of drugs; however, it is not scalable for large-scale implementation and lacks an analysis of transaction costs.

Fig.7. Different Language

The system analyzed the uploaded image and identified the plant as healthy with 100% detection accuracy. It also provides valuable recommendations, including organic treatment tips such as the use of organic compost, preventive measures like regular plant inspection, proper watering, and balanced fertilization, along with crop rotation suggestions to maintain soil fertility and overall plant health.

This image highlights the multilingual support capability of the platform. The diagnosis results and recommendations are displayed in Gujarati, demonstrating improved accessibility for regional farmers. The AI-based system ensures that essential agricultural guidance is available in multiple languages, helping to overcome language barriers and making smart farming solutions more inclusive for diverse farming communities

V. DRAWBACKS OF EXISTING SYSTEM

Existing plant disease detection systems face several limitations that affect their practical implementation in real-world agricultural environments. First, image quality may vary due to inconsistent lighting conditions, poor camera resolution, or improper angles when farmers capture leaf images, which can significantly reduce detection accuracy. Improved image preprocessing and enhancement techniques can help overcome this issue. Second, ensemble models, although highly accurate, often require greater computational resources and may produce slower response times, causing delaysin real-time disease detection where immediate action is necessary. Reducing latency would make such systems more practical for field deployment. Third, many existing models are trained on limited datasets and may not perform effectively across all crop types or rare disease categories. Therefore, more diverse datasets and continuous fine-tuning are required to improve model generalization, robustness, and reliability.

VI. 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 (Efficien-tNet, 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

Fig.8. DL Architecture

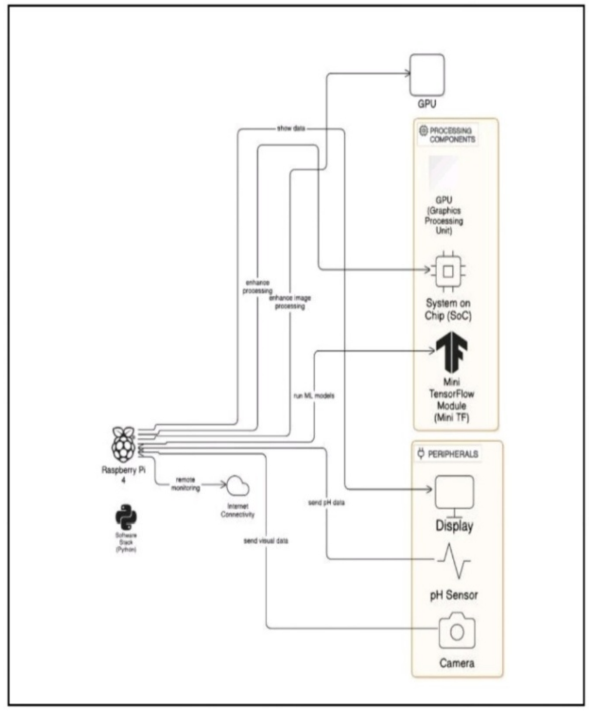


Fig.9. System Architecture

VII. CONCLUSION

The project develops an ensemble-based plant disease detection system using lightweight deep learning models on Raspberry Pi 5, optimizing performance with Mini-Tensor 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 in resource-constrained agricultural environments

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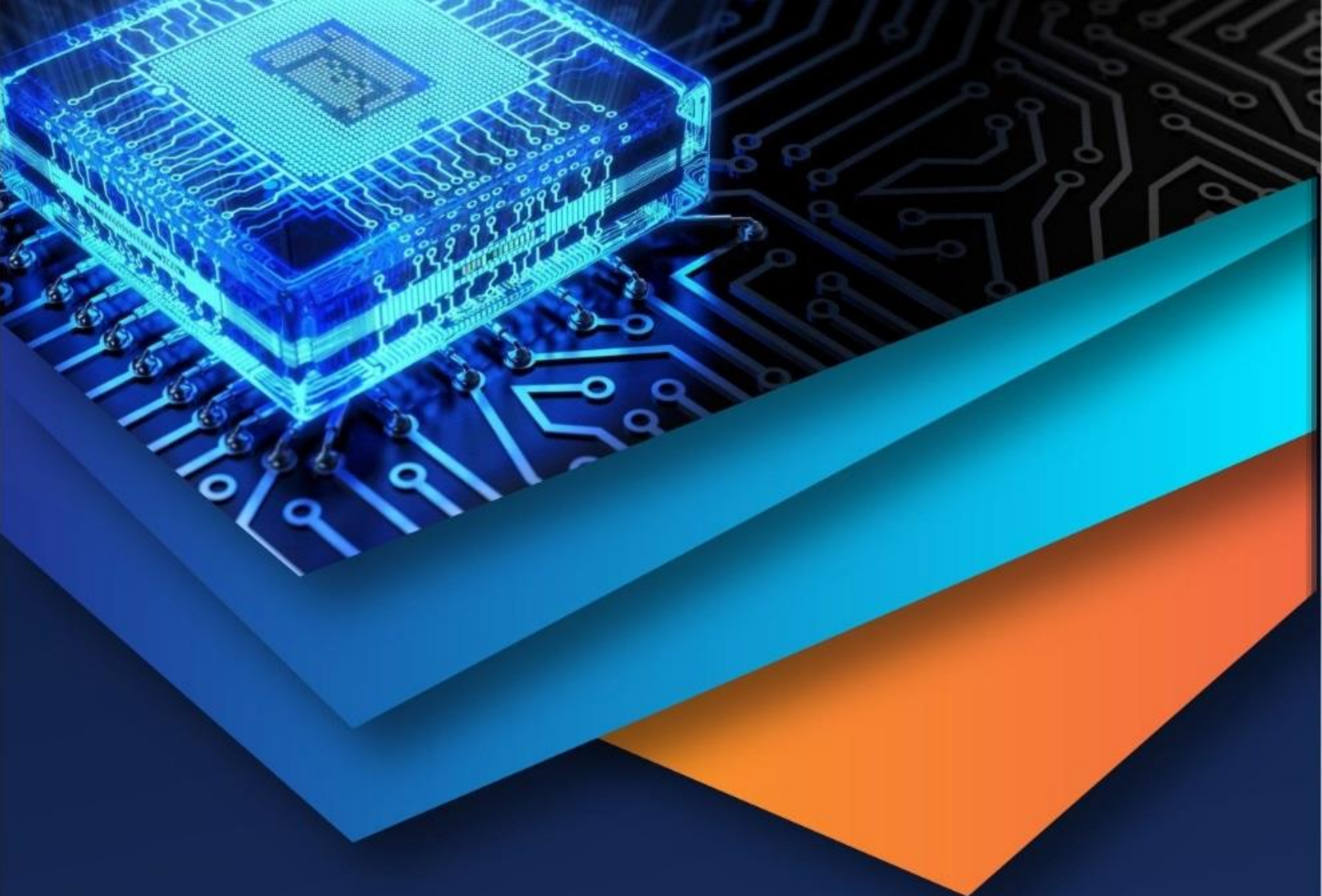

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