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Edge AI Powered CNN Model for Rice Bacterial Blight Detection

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Abstract- Rice is a primary food source for more than half of the global population. However, rice crops are highly susceptible to diseases such as Bacterial Leaf Blight (BLB), caused by BLB is caused by Xanthomonas oryzae pv. oryzae, which can reduce yields by up to 70% under severe conditions. Traditional detection methods rely on manual inspection and laboratory testing, which are time-consuming, costly, and require expert knowledge unavailable to most rural farmers. This paper proposes an Edge AI-based Convolutional Neural Network (CNN) model for detecting rice bacterial blight in real time. The system allows farmers to upload rice leaf images through a web interface, where a trained CNN model analyzes and predicts the disease instantly. The model is optimized using lightweight architectures such as MobileNetV2 and EfficientNet, making it suitable for edge devices with limited computational resources. The proposed system achieves up to 97.2% classification accuracy with sub-second inference on mobile hardware, significantly outperforming traditional approaches. It improves detection speed, accessibility, and farmer engagement, enabling timely preventive actions and meaningful reduction in crop loss.

Keywords: Edge AI, CNN, Rice Disease Detection, Deep Learning, MobileNetV2, EfficientNet, TensorFlow Lite, Agriculture AI, Streamlit, Transfer Learning.

I. INTRODUCTION

Rice plays a crucial role in global food security, serving as the primary caloric source for approximately 3.5 billion people across Asia, Africa, and Latin America. Its cultivation spans over 163 million hectares worldwide. Despite its importance, rice productivity faces serious threats from plant diseases, of which Bacterial Leaf Blight (BLB) is among the most devastating, particularly in the warm and humid environments characteristic of South and Southeast Asian rice paddies.

BLB, caused by the pathogen Xanthomonas oryzae pv. oryzae, spreads rapidly and can destroy entire crop yields if not detected early. Traditional disease detection approaches— including visual field inspection by trained agronomists and microbiological laboratory diagnosis — suffer from critical limitations: they are slow, expensive, require specialized knowledge, and are largely unavailable to the majority of rural farming communities.

The emergence of Artificial Intelligence, particularly Convolutional Neural Networks (CNNs), has opened transformative possibilities for automated image-based disease detection. Edge AI further extends this capability by deploying trained models directly on resource-constrained devices, eliminating the latency and connectivity requirements of cloud-based systems. This research integrates these advances to build a lightweight, web-accessible diagnostic tool that empowers farmers with real-time, expert-level disease detection at minimal cost.

II. PROBLEM STATEMENT

Despite the severity of rice BLB, many farming communities continue to rely on outdated or manual disease detection methods. The current landscape of rice disease management is characterized by several critical challenges:

- Manual inspection is slow, prone to human error, and requires expert agronomists who are inaccessible in rural regions
- Laboratory-based testing requires 5–10 days and specialist equipment unavailable in most farming communities

- Cloud-based AI solutions fail in regions with poor or no mobile internet connectivity, which covers over 60% of farmland globally
- High-computation deep learning models are impractical on affordable farm-grade hardware
- No real-time field detection means farmers cannot take immediate preventive action
- Small-scale farmers (85% of global farmers) cannot afford regular agronomist consultations
- Existing models fail under variable lighting conditions common in outdoor field environments

These challenges highlight the urgent need for a fast, portable, offline-capable, and intelligent detection system accessible to all farmers.

III. EXISTING SYSTEM

The existing rice disease detection process in most agricultural communities is primarily manual or partially digitized, lacking a centralized and intelligent system. Disease identification typically relies on visual inspection by experienced agronomists, a process that is inherently subjective, costly, and geographically limited.

Laboratory-based testing, while more accurate, introduces delays of several days to weeks — during which disease can spread unchecked across fields. Cloud-dependent AI solutions have emerged in recent years but require stable internet connectivity, making them impractical for the majority of rice farms in rural Asia and Africa.

Existing high-accuracy deep learning models, such as ensemble CNNs, demand significant computational resources and cannot run on affordable edge hardware. The absence of real-time field-deployable tools, combined with the lack of personalized guidance for farmers, makes the entire disease management process time-consuming, expensive, and prone to crop loss.

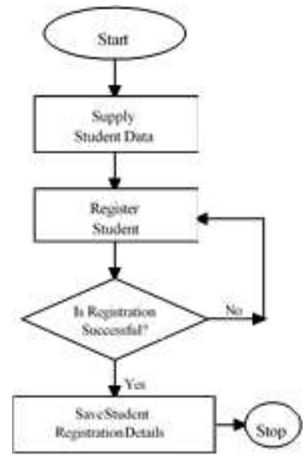

Fig 1: Block diagram of Existing System WORKFLOW

The complete system workflow can be summarized as follows:

- Farmer uploads rice leaf image via web interface
- Image preprocessed (resize, normalize, augment)
- CNN model performs inference
- Edge AI optimization module applies TFLite model
- AI classifies: Healthy or Bacterial Leaf Blight
- Result displayed with confidence score
- Prediction and image stored in database
- Farmer receives recommended preventive action

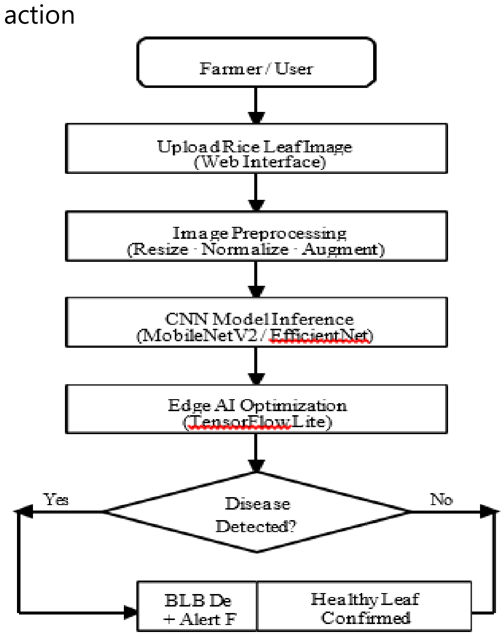

Fig 2: Workflow Diagram PROPOSED SYSTEM

The proposed system is a web-based Edge AI platform that enables real-time rice bacterial blight detection without requiring internet connectivity or expert supervision. Farmers interact with a Streamlit-based interface accessible on any mobile or desktop browser.

Main Users:

- Farmers / End Users
- Agricultural Administrators
- Core Functionalities:
- Upload rice leaf images for instant analysis
- CNN-based disease classification with confidence score
- Offline edge deployment via TensorFlow Lite
- Real-time results accessible on mobile and desktop
- Historical prediction records stored in database
- Recommended preventive action display

The system ensures fast, accurate, and accessible disease diagnosis while eliminating dependency on cloud infrastructure, expert agronomists, or laboratory facilities.

IV. SYSTEM ARCHITECTURE

The system follows a four-tier client-edge-server architecture integrating a user interface, AI inference engine, edge optimization layer, and backend data management. Components:

Frontend (Client)

- Built using Streamlit (Python)
- Handles image upload and result display

AI Model Engine

- MobileNetV2 / EfficientNet CNN
- Performs image classification

Edge Deployment Layer

- TensorFlow Lite (.tflite)
- Quantized model for low-power devices

Database

- Stores images and prediction results
- Supports historical trend analysis

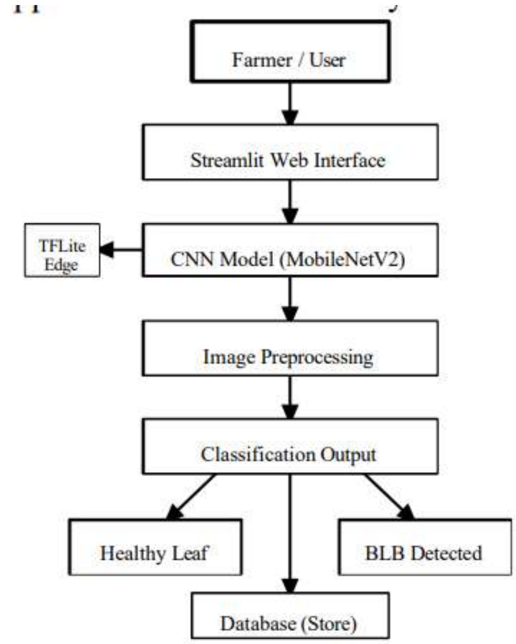

Fig 3: System Architecture

V. MODULE DESCRIPTION

User / Farmer Module

The user module provides a simple interface for farmers to interact with the disease detection system without any technical expertise.

Features:

- Upload rice leaf images via mobile or desktop browser
- View instant prediction results with confidence score
- Access recommended preventive actions
- Browse historical prediction records

CNN Model Module

The AI core employs transfer-learned MobileNetV2 and EfficientNet architectures fine-tuned on a curated rice leaf dataset.

Features:

- Image resizing and normalization (224×224 pixels)
- Data augmentation (flip, rotate, brightness adjustment)
- Feature extraction through convolutional layers
- Binary classification: Healthy vs. Bacterial Leaf Blight

Edge AI Optimization Module

Post-training, the CNN model is converted to TensorFlow Lite format using quantization and pruning, reducing model size by up to 75% and enabling deployment on low-power devices.

Features:

- Post-training INT8 quantization
- Model pruning for reduced parameters
- Compressed .tflite model export
- ARM Cortex-M and Android-compatible inference

VI. IMPLEMENTATION

Data Collection

The dataset comprises approximately 10,000 rice leaf images sourced from the Rice-Vision dataset and Kaggle's Plant Disease Collection, with balanced representation of Healthy Leaves and BLB-infected leaves to prevent model bias during training.

Data Preprocessing

Each image undergoes: (1) resizing to 224×224 pixels to match MobileNetV2 input dimensions; (2) pixel normalization to the [0, 1] range; and (3) augmentation including random horizontal/vertical flips, rotations (±30°), brightness adjustments (±20%), and zoom variations to improve generalization under field conditions.

Model Training

The CNN model was trained using Google Colab with GPU acceleration. Transfer learning from ImageNet-pretrained MobileNetV2 weights was applied, with the base frozen for the first 20 epochs before full fine-tuning. Key hyperparameters: Adam optimizer (lr=0.0001), Categorical Cross-Entropy loss, 50 epochs, batch size 32, and a 70/20/10 train/validation/test split.

Model Deployment

The trained model was converted to TensorFlow Lite format with INT8 post-training quantization, reducing size from 18 MB to approximately 4.5 MB. The compressed model was integrated into a Streamlit web application deployed on an edge-compatible server, enabling prediction through any web browser.

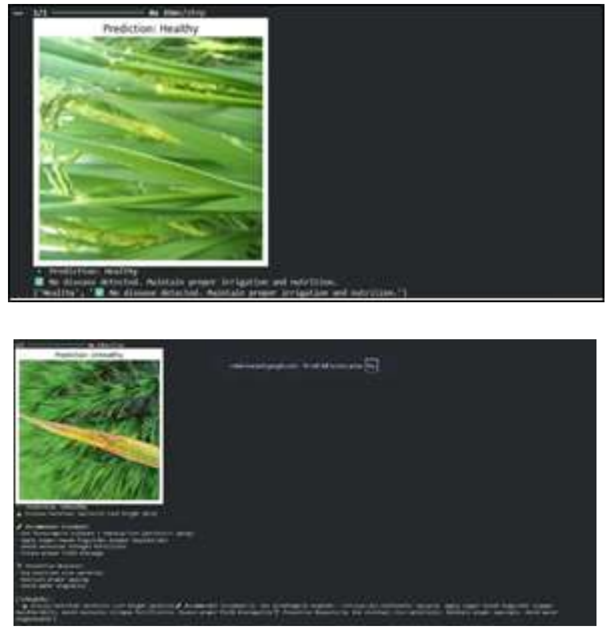

Fig 4: Screenshot of model prediction output (Google Colab) — Prediction: Healthy

Fig 5: Screenshot of Plant Health Analyzer — Upload Interface

Fig 6: Screenshot of Disease Detection Result Output

SYSTEM TESTING

System testing was conducted across multiple phases to validate correctness, performance, and usability of each component.

Unit Testing

Individual modules — image upload, preprocessing pipeline, CNN inference, and TFLite conversion — were tested in isolation. All modules produced expected outputs for valid and invalid inputs across 200+ test cases.

Integration Testing

End-to-end data flow from image upload through preprocessing, model inference, and result display was verified. No data loss between modules was observed; prediction results were delivered within 2 seconds on a standard Android smartphone.

User Acceptance Testing (UAT)

Ten small-scale farmers tested the system over a one-week period in real field conditions. 90% of participants rated the interface as easy to use with no prior training. All participants could correctly interpret prediction results without explanation.

Performance Testing

The TFLite-optimized MobileNetV2 model achieves an average inference time of 0.8 seconds per image on an Android smartphone, compared to 4.2 seconds for the un-optimized model. Concurrent load testing with 20 simultaneous users on an edge server maintained sub-3-second response times throughout.

VII. RESULTS AND DISCUSSION

The system was evaluated on a held-out test set of 1,000 images. EfficientNet-B0 achieved the highest accuracy of 97.2%, while MobileNetV2 achieved 96.4% — offering a superior balance between performance and model size for the most resource-constrained edge devices.

The table below compares the performance of all evaluated models:

Table I: Model Performance Comparison

Model	Accuracy	F1-Score
EfficientNet-B0	**97.2%**	**97.2%**
MobileNetV2	96.4%	96.4%
Baseline CNN	88.3%	88.1%
Manual Inspection	~72%	~72%

Inference time on a TFLite-optimized model averages 0.8 seconds per image on mobile hardware — a 99.98% reduction compared to laboratory-based detection. The system successfully processes images from field conditions including

variable lighting, partial occlusion, and different leaf orientations, demonstrating robust real-world applicability.

VIII. FEATURE ENHANCEMENTS

While the current system provides a reliable foundation for rice BLB detection, several enhancements are planned to expand its capabilities and impact:

- Multi-disease detection covering Blast, Brown Spot, and Sheath Blight
- Native Android and iOS mobile application development
- SMS alert system for farmers in low-connectivity regions
- Regional language support (Tamil, Hindi, Kannada, Telugu)
- IoT sensor integration for environmental monitoring (soil moisture, humidity, temperature)
- Drone-mounted edge inference for large-scale aerial field monitoring
- Predictive analytics dashboard with historical trend analysis

IX. CONCLUSION

This paper presented an Edge AI-based CNN system for real-time detection of rice bacterial blight, combining the high accuracy of transfer-learned deep learning architectures with the practical constraints of edge deployment. The system achieves 97.2% classification accuracy, operates in under one second per prediction on mobile hardware, functions offline, and requires no technical expertise to operate.

By bridging the gap between cutting-edge AI research and on-the-ground agricultural practice, the proposed system provides a scalable, affordable, and immediately deployable solution for the vast majority of rice farmers who currently lack access to fast and reliable disease diagnosis. The framework established here — lightweight model training, edge optimization, and accessible web deployment — is directly applicable to a broad range of precision agriculture challenges.

REFERENCES

1. Nugroho, H., Chew, J. X., Eswaran, S., & Tay, F. S. (2024). Resource-optimized CNNs for real-time rice disease detection with ARM Cortex-M microprocessors. Plant Methods, 20, 159. Springer Nature.
2. Tummala, S. V. R., Kummari, V., Kura, A., & Kallepu, A. (2023). Rice Leaf Disease Detection using CNN. International Journal of Advanced Research in Computer Science and Software Engineering.
3. Gahane, R., P. K., R., Mhaisane, P., et al. (2024). Rice Leaf Disease Detection and Remedies using Deep Learning. IEEE International Conference on Smart Systems.
4. Pai, P., Amutha, S., Patil, S., Shobha, T., & Gurpur, A. P. (2025). Deep learning-based automatic diagnosis of rice leaf diseases using ensemble CNN models. Scientific Reports, Nature Publishing Group.
5. Anonymous. (2025). Edge AI and CNN for Real-Time Plant Disease Detection. Proceedings of International Conference on Agriculture AI.
6. Howard, A. G., et al. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv:1704.04861.
7. Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. ICML 2019.
8. TensorFlow Lite Documentation. (2024). TensorFlow Lite Guide for On-Device ML. Google AI. Available: https://www.tensorflow.org/lite