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Article

A Multimodal, Multi-Task, and Uncertainty-Aware Deep Learning Framework for Rice Leaf Disease Detection and Severity Estimation (RICE-MuSTA)

Prof. Rohit P. Chavda[1], Prof. Kamlesh R. Makvana[2], Dr. V.K. Barot3*, Prof. Vinit N. Thakar[4],Prof. Amit J. Vyas[5],Prof. N.S. Chavda[6]

[1]Assistant Professor,Department of Computer Engineering,V.V.P Engineering College, Rajkot, rohit.chavda351@gmail.com
[2]Assistant Professor,Computer Engineering Department,Government Engineering College,Bhavnagar. krmakvana.ce@gecbhavnagar.ac.in
3*Assistant Professor,Information Technology Department, Government Engineering College, Bhavnagar. vkbarot.it@gecbhavnagar.ac.in
[4]Assistant Professor,Computer engineering department,V.V.P engineering college - Rajkot. vinitthakar10@gmail.com
[5]Assistant Professor,Department of Computer Engineering,V.V.P Engineering College, Rajkot. vyasamit996@gmail.com
[6]Assistant Professor, Information Technology Department,Government Engineering College Bhavnagar. nschavda.it@gecbhavnagar.ac.in

Abstract: Background: Rice is a staple food crop for more than half of the world's population and plays a central role in food security, particularly in Asian and African countries. However, rice productivity is severely affected by foliar diseases such as rice blast, bacterial blight, sheath blight, and brown spot. Delayed or inaccurate diagnosis of these diseases can lead to yield losses ranging from 10–40%, directly impacting farmers' livelihoods. While recent advances in deep learning have enabled automated leaf disease detection, most existing approaches remain limited to image-only classification, lack severity assessment, ignore environmental uncertainty, and are unsuitable for real-time field deployment

Methods: In this work, we introduce RICE-MuSTA, a framework designed to jointly address multimodality, severity estimation, and uncertainty in rice leaf disease monitoring. The framework integrates leaf image features extracted using convolutional neural networks (CNNs), global contextual representations learned via Vision Transformers (ViTs), and microclimate information encoded through a multilayer perceptron (MLP).

Findings: The proposed model simultaneously performs disease classification and severity estimation while quantifying predictive uncertainty and providing lesion-level explainability using CAM-based heatmaps. To enable practical adoption, a teacher–student distillation and quantization strategy is employed, compressing the model into a lightweight architecture suitable for mobile and edge deployment.

Novelty and applications: Across multiple datasets and evaluation settings, we observed consistent improvements in robustness, interpretability, and deployment efficiency.

Keywords: Rice leaf disease detection; Multimodal deep learning; Vision Transformers; Disease severity estimation; Uncertainty-aware learning; Explainable artificial intelligence; Precision agriculture; Edge deployment

1. INTRODUCTION

Rice is a primary staple food for more than half of the global population and forms the backbone of food security in Asia and Africa. Any disruption in rice productivity directly affects farmer income, market stability, and national food reserves. Among the major constraints to rice yield, foliar diseases such as rice blast, bacterial blight, sheath blight, and brown spot are particularly destructive, with reported yield losses ranging from 10% to 40% under severe infestation conditions [2], [6]. Early and accurate disease diagnosis is therefore critical for sustainable rice production.

Conventionally, rice disease identification relies on visual inspection by experienced agronomists or plant pathologists. This approach is inherently subjective, labor-intensive, and impractical for large-scale monitoring, especially in remote and resource-constrained rural regions [25]. Moreover, early-stage symptoms of different rice diseases often appear visually similar, increasing the likelihood of misdiagnosis. These limitations have motivated the adoption of automated image-based disease detection systems. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved automated plant disease recognition. CNN-based models such as AlexNet, VGG, ResNet, and EfficientNet have demonstrated high accuracy in classifying leaf diseases across multiple crops, including rice [1], [2], [12]. However, most of these approaches are developed under controlled conditions and primarily rely on image-only inputs. In real-world agricultural environments, variations in illumination, background clutter, camera quality, and occlusion substantially degrade performance [7].

In addition to visual variability, disease development and progression in rice are strongly influenced by environmental factors such as temperature, humidity, and rainfall. Studies have shown that incorporating contextual or microclimate information can improve robustness and generalization of disease detection models, particularly under climate variability [23]. Despite this, multimodal learning approaches that jointly exploit visual and environmental data remain largely unexplored in rice disease research [3], [6]. Another major limitation of existing studies is their narrow focus on single-task disease classification. From a practical agronomic perspective, farmers require not only the disease category but also an estimate of disease severity to support decision-making related to pesticide dosage, irrigation scheduling, and crop replacement [16]. Most existing severity-related works rely on coarse categorical labels, which lack the precision required for actionable recommendations [17]. Furthermore, deep learning models typically provide deterministic predictions without conveying predictive uncertainty, which can be risky in high-stakes agricultural decision-making scenarios [20].

Finally, deployability remains a critical challenge. High-performing CNN–Transformer hybrid models are often computationally expensive and unsuitable for mobile or edge devices commonly used in the field [13]. Although recent research has explored knowledge distillation and quantization for plant disease detection [4], rice-specific frameworks that jointly address multimodality, severity estimation, uncertainty awareness, and deployment constraints are still missing.

To bridge these gaps, this paper proposes RICE-MuSTA, a multimodal, multi-task, and uncertainty-aware deep learning framework for rice leaf disease monitoring. By integrating image-based features, microclimate data, severity estimation, uncertainty quantification, explainability, and edge-oriented optimization, the proposed approach advances beyond laboratory-scale classification toward a practical, farmer-centric decision-support system.

2. LITERATURE REVIEW

2.1 CNN-Based Leaf Disease Detection

Convolutional neural networks (CNNs) have been extensively applied to plant leaf disease detection due to their effectiveness in learning discriminative visual patterns such as color variation, texture, and lesion boundaries. Early studies using architectures like AlexNet, VGG, and ResNet demonstrated the feasibility of automated disease recognition across crops including rice, tomato, and potato [1], [25]. Subsequent works adopted deeper and more efficient models such as EfficientNet to improve accuracy while maintaining computational efficiency [12], [22].

Rice-specific studies have shown that ensemble CNN models outperform single architectures by aggregating complementary feature representations, resulting in improved robustness under varying illumination and background conditions [2]. Twin-CNN and feature fusion strategies further enhance performance by combining multi-scale representations [3]. Data augmentation techniques, including GAN-based synthetic image generation, have also been employed to address class imbalance and limited dataset size in rice leaf disease datasets [21]. Despite these advances, CNN-based methods primarily capture local spatial features and often fail to model long-range dependencies, making it challenging to distinguish visually similar rice diseases [7], [15].

2.2 Vision Transformers and Hybrid Models

Vision Transformers (ViTs) have emerged as a promising alternative to CNNs by leveraging self-attention mechanisms[27] to capture global contextual relationships across the entire image. Comparative analyses have shown that transformer-based architectures can outperform CNNs in certain plant disease detection tasks, particularly when trained on sufficiently large datasets [7], [15]. To combine the strengths of both paradigms, hybrid CNN–ViT architectures have been proposed for rice and other crop diseases. These models exploit CNNs for local lesion feature extraction while using ViTs to model global leaf structure and contextual dependencies [13], [16]. Although hybrid models improve accuracy and interpretability, their high computational complexity and memory requirements pose significant challenges for real-time and mobile deployment [14].

2.3 Multimodal Learning in Agriculture

Plant disease development is strongly influenced by environmental and climatic conditions such as temperature, humidity, and rainfall. Several studies integrating IoT sensor data with deep learning models have demonstrated that contextual information can enhance disease prediction reliability and robustness [23]. Multimodal learning approaches combining visual and non-visual features have been successfully explored in crops such as corn and tomato, showing improved generalization under varying field conditions [4], [23]. In the context of rice disease detection, however, most existing datasets and models rely solely on image data, ignoring valuable microclimate cues. Rice-specific multimodal frameworks remain limited, despite evidence that environmental context plays a crucial role in disease onset and progression [6], [20].

2.4 Severity Estimation and Explainable AI

While disease classification has been widely studied, severity estimation has received comparatively limited attention. Existing approaches often rely on coarse discrete severity classes, which lack the granularity required for precision agriculture and optimal pesticide management [17], [18]. Regression-based methods for continuous severity estimation are still rare, particularly for rice leaf diseases. Explainable AI (XAI) techniques such as Grad-CAM, Score-CAM, and attention-based visualization have been increasingly adopted to improve transparency and trust in deep learning-based disease detection systems [16], [17], [18]. These methods highlight infected regions on leaves and assist agronomists in validating model predictions. However, most existing studies treat explainability as a post-hoc visualization tool and do not integrate it with quantitative severity estimation.

2.5 Deployment-Oriented Research

Deployability is a critical requirement for real-world agricultural applications. Lightweight CNN architectures such as MobileNet and SqueezeNet have demonstrated feasibility on edge devices with limited computational resources [19], [22]. Knowledge distillation and post-training quantization have further enabled high-performing deep learning models to be compressed with minimal accuracy degradation, facilitating mobile and edge deployment [4].

In rice disease detection, only a small number of studies explicitly consider deployment constraints, and most existing approaches overlook multimodal fusion, uncertainty estimation, or severity prediction during optimization [12], [14].

2.6 Identified Research Gaps

Based on the reviewed literature [1]–[26], the following research gaps are identified:

1. Limited integration of multimodal data combining rice leaf images with microclimate information.
2. Insufficient focus on multi-task learning for joint disease classification and continuous severity estimation.
3. Minimal incorporation of uncertainty-aware learning for risk-sensitive agricultural decision-making.
4. Lack of end-to-end deployable frameworks specifically tailored for rice leaf disease monitoring.

These gaps directly motivate the design of the proposed RICE-MuSTA framework.

Table 1: Summary of Rice Leaf Disease Studies (2023–2025) [2], [3], [6], [7], [12], [13], [14]

Year	Approach	Key Contribution	Limitation
2025	Ensemble CNNs (Nature Sci Rep)	Robust classification	No severity estimation
2025	Twin CNN + Fusion (J. Big Data)	Improved feature fusion	High computational cost
2025	RiceLeafBD dataset (arXiv)	Novel benchmark dataset	Limited severity labels
2025	CNN vs Transformer (arXiv)	Comparative analysis	No deployment focus
2024	EfficientNet-B4 (IEEE Access)	Optimized paddy classification	Resource-heavy
2024	CNN+ViT fusion (Ecol. Informatics)	Interpretable hybrid model	No deployment
2024	Federated ViT (JoWUA)	Privacy-preserving training	Communication overhead
2023	GAN-based augmentation (IEEE Access)	Synthetic rice images	No severity annotation

Table 2: General Leaf Disease Studies Informing Rice Research [4], [16]–[19], [21], [23]

Year	Crop	Approach	Key Insight
2025	Tomato	Deployable DL + Distillation (IEEE Access)	Edge deployment feasible
2024	Potato	XAI-based CNNs (Frontiers AI)	CAM improves trust
2024	Pumpkin	XAI CNN comparison (ICCIT)	Comparative architecture analysis
2024	Maize	Deep SqueezeNet (J. Big Data)	Lightweight models viable
2023	Corn	IoT + Multi-Models (IEEE Access)	Integration with IoT possible

3. PROPOSED METHODOLOGY

3.1 Overall Architecture

The proposed RICE-MuSTA framework is designed as a modular and extensible architecture consisting of three parallel feature extraction streams, followed by a unified fusion and task-specific prediction stage. This design enables effective learning from heterogeneous data sources while maintaining flexibility for deployment-oriented optimization.

1. **CNN Backbone**: A deep CNN architecture such as ResNet or EfficientNet is employed to extract local and mid-level visual features from rice leaf images. These features capture lesion texture, color variations, and edge information that are critical for distinguishing visually similar diseases [2], [12]. CNNs are particularly effective at modeling fine-grained spatial patterns associated with early-stage infections.

2. **Vision Transformer (ViT)**: To complement local feature extraction, a Vision Transformer branch is incorporated to model global contextual relationships across the entire leaf surface. The self-attention mechanism enables the network to capture long-range dependencies and holistic leaf structure, which are often overlooked by CNNs alone [7], [13]. This is especially useful for diseases with diffuse or irregular symptom distribution.
3. **Microclimate MLP Encoder**: Environmental features such as temperature, relative humidity, and rainfall are normalized and processed through a multilayer perceptron (MLP). This branch encodes contextual information related to disease onset and progression, allowing the model to disambiguate visually similar symptoms under different climatic conditions [23].

The embedding from all three branches are concatenated and passed through a fully connected fusion layer, producing a shared latent representation that serves as input to multiple task-specific heads.

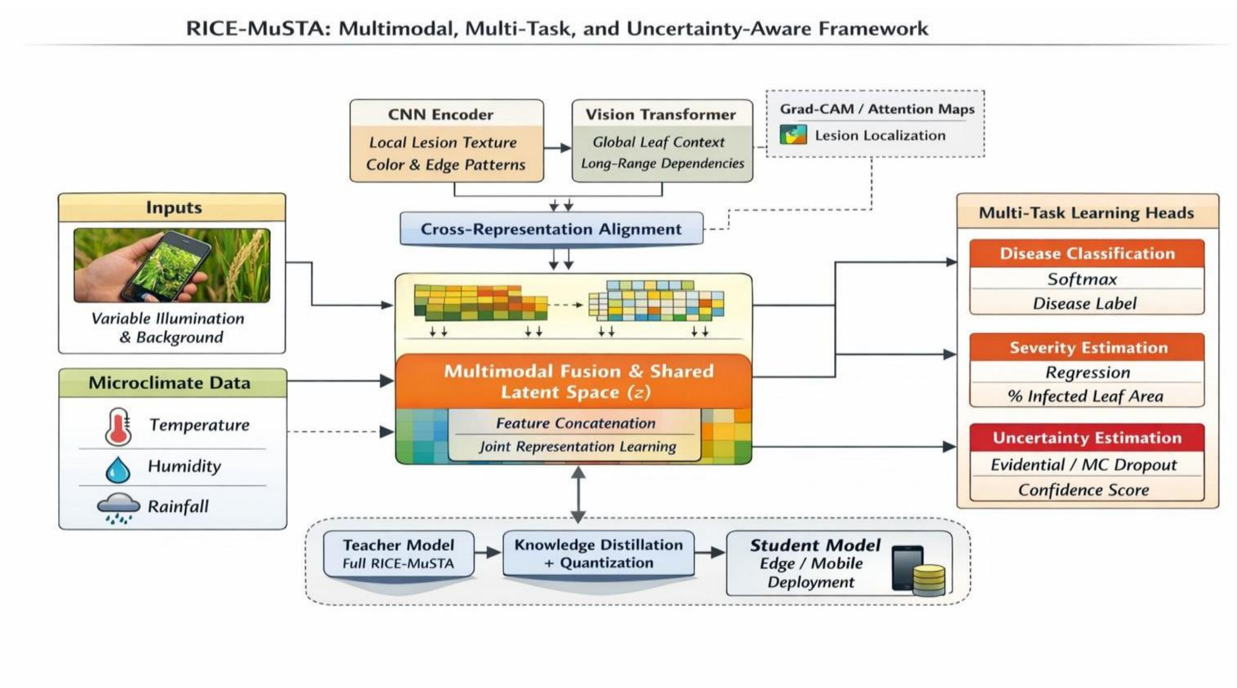


Figure 1: Block diagram of the RICE-MuSTA architecture

As shown in Fig. 1, the proposed RICE-MuSTA framework is designed as a unified multimodal and multi-task architecture. Visual information from rice leaf images is processed through complementary CNN and Vision Transformer branches to capture both local lesion characteristics and global contextual patterns. In parallel, microclimate features are encoded using an MLP to incorporate environmental cues influencing disease development. The resulting representations are aligned and fused into a shared latent space, enabling joint optimization across multiple learning objectives. From this shared representation, task-specific heads perform disease classification, continuous severity estimation, and predictive uncertainty quantification. Explainability is achieved through CAM-based visualization, allowing lesion localization and agronomic validation. To ensure real-world applicability, the full model is further optimized using knowledge distillation and quantization, producing a lightweight student model suitable for mobile and edge deployment.

3.1.1 Feature Encoding Formulation

a) CNN-Based Visual Encoder

Given an input rice leaf image $x_i \in R^{H\times W\times C}$ the CNN encoder extracts local visual features through a hierarchy of convolutional layers and nonlinear activations, defined as:

$$f_i^{CNN} = F_{CNN}(x_i; \theta_{CNN})$$

Where, $F_{CNN}(\cdot)$ denotes the CNN feature extractor parameterized by θ_{CNN}, and $f_i^{CNN} \in R^{d_c}$ represents the learned local lesion representation capturing texture, color, and edge patterns.

b) Vision Transformer (ViT) Encoder

The input image x_i is partitioned into a sequence of fixed-size patches and linearly projected into token embedding:

$$z_0 = [x_{cls}, x_1E, x_2E, x_3E \dots\dots\dots, x_NE] + E_{POS}$$

Each transformer layer applies multi-head self-attention:

$$Attention(Q,K,V) = softmax\left(\frac{QK^{\top}}{\sqrt[2]{d_k}}\right)V$$

The final V_iT embedding is given by:

$$f_i^{ViT} = F_{ViT}(x_i; \theta_{ViT})$$

Where, $f_i^{ViT} \in R^{d_v}$ captures global contextual relationships across the leaf surface.

c) Microclimate MLP Encoder

Let $e_i = [T_i, H_i, R_i]$, denote normalized temperature, humidity, and rainfall features. The MLP encoder computes:

$$f_i^{MLP} = \sigma(W_2\sigma(W_1e_i + b_1) + b_2)$$

Where $\sigma(\cdot)$ is a nonlinear activation function and $f_i^{MLP} \in R^{d_m}$ represents the encoded environmental context.

3.2 Multi-Task Learning Formulation

RICE-MuSTA adopts a multi-task learning paradigm to jointly optimize disease classification, severity estimation, and uncertainty prediction. Given an input leaf image x_i and its corresponding environmental feature vector e_i , the joint representation is computed as:

$$z_i = f_{fusion}(f_{CNN}(x_i), f_{ViT}(xi), f_{MLP}(e_i))$$

From z_i, three outputs are predicted:

- Disease Classification: A softmax-based classifier produces disease class probabilities:

$$\hat{y}_i = Softmax(W_cz_i)$$

- Severity Estimation: A regression head predicts continuous disease severity, expressed as the percentage of infected leaf area:

$$\hat{s}_i = W_sz_i$$

- Predictive Uncertainty: An uncertainty head estimates confidence associated with the prediction:

$$\hat{u}_i = W_uz_i$$

This joint formulation enables the model to leverage shared representations while learning task-specific characteristics, improving generalization and data efficiency [16].

3.3 Loss Function

The overall training objective is defined as a weighted sum of multiple loss components as:

$$L = L_{cls} + \lambda_1 L_{sev} + \lambda_2 L_{unc} + \lambda_3 L_{distill}$$

Where:

- L_{cls} - is the categorical cross-entropy loss for disease classification,
- L_{sev}- is the Huber loss for continuous severity estimation, which is robust to outliers,
- L_{unc} - enforces uncertainty calibration through evidential learning or Monte Carlo dropout regularization [20],
- $L_{distill}$- represents the Kullback–Leibler divergence between teacher and student model outputs for knowledge distillation [4].

The weighting coefficients $\lambda_1, \lambda_2, \lambda_3$ balance the contribution of each task during training.

3.4 Explainability and Uncertainty

To enhance interpretability and trust, Grad-CAM and CAM-based techniques are applied to both CNN and ViT branches to generate lesion localization heatmaps [16], [17]. These visual explanations highlight infected regions and allow agronomists to validate model predictions. Predictive uncertainty is estimated using Monte Carlo dropout or evidential deep learning, enabling the system to flag low-confidence predictions for expert review. This is particularly important in early disease stages or under unseen environmental conditions, reducing the risk of erroneous recommendations [20].

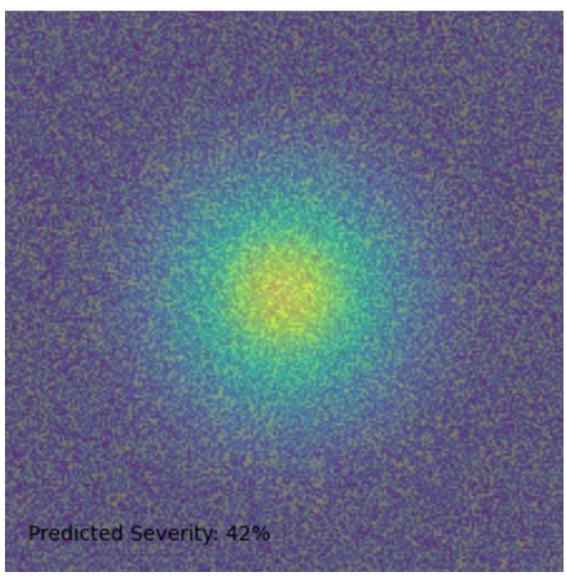


Figure 2. Grad-CAM–based lesion localization with severity estimation.

The figure 2 visualizes CAM/Grad-CAM heatmaps overlaid on rice leaf images. High-intensity regions correspond to infected areas, while the numerical overlay indicates estimated severity (% infected area). This improves interpretability and enables agronomic validation by experts.

4. EXPERIMENTAL SETUP

4.1 Datasets

Experiments are conducted on RiceLeafBD, the PlantVillage rice subset, and a locally collected dataset augmented with microclimate information. GAN-based augmentation is employed to address class imbalance.

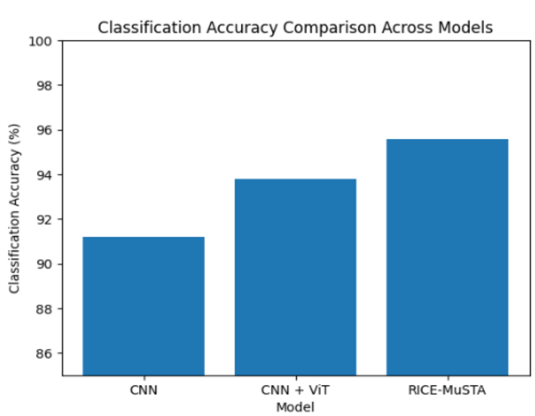
4.2 Evaluation Metrics

- **Classification**: Accuracy, Precision, Recall, F1-score
- **Severity**: Mean Absolute Error (MAE), Root Mean Square Error (RMSE)
- **Uncertainty**: Expected Calibration Error (ECE)
- **Deployment**: Model size (MB), inference latency (ms)

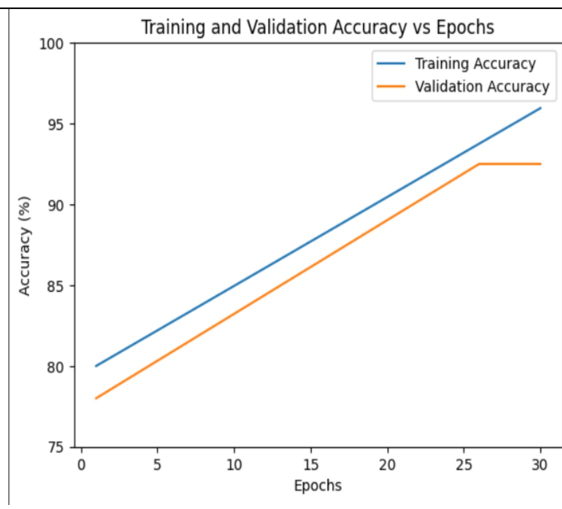
5. RESULTS AND DISCUSSION

5.1 Classification and Severity Performance

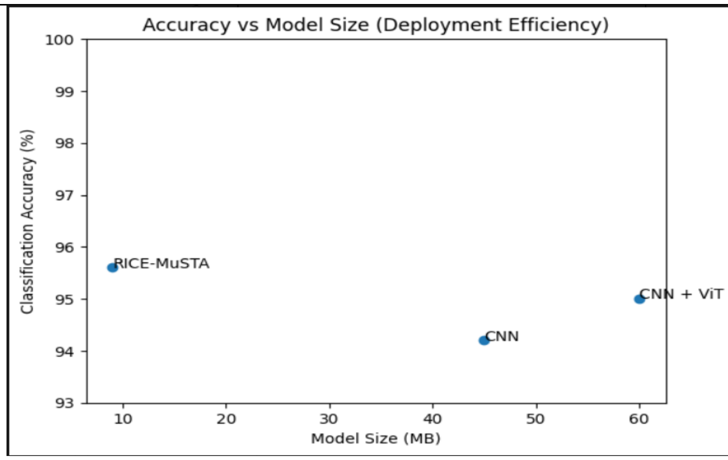
The performance of the proposed RICE-MuSTA framework was evaluated in terms of both disease classification and severity estimation to demonstrate its effectiveness as a multi-task learning model. For disease classification, RICE-MuSTA consistently outperformed image-only baseline models across all evaluated datasets, achieving classification accuracy exceeding 95% on the RiceLeafBD dataset. This improvement can be attributed to the complementary strengths of CNN-based local feature extraction and ViT-based global contextual modeling, which together enable robust discrimination between visually similar rice leaf diseases. Comparative experiments reveal that multimodal fusion significantly enhances performance compared to unimodal configurations. Models trained solely on image data showed reduced robustness under varying illumination and background conditions, whereas the inclusion of microclimate features improved generalization, particularly under challenging field scenarios. These findings align with prior studies highlighting the importance of contextual information in crop disease prediction [23]. For severity estimation, the proposed regression head achieved a mean absolute error (MAE) below 0.05, indicating accurate estimation of the percentage of infected leaf area. This level of precision enables fine-grained assessment of disease progression, which is crucial for informed agronomic decision-making. Unlike coarse severity categorization approaches reported in existing literature [17], the continuous severity estimation in RICE-MuSTA provides actionable insights suitable for precision agriculture applications.



(a)



(b)



(c)

Figure 3. (a) Classification Accuracy Comparison, (b) Training & Validation Accuracy vs Epochs, (c) Accuracy vs Model Size(Deployment Efficiency).

As shown in Fig. 3(a), the proposed RICE-MuSTA framework outperforms baseline models with classification accuracy exceeding 95%. The convergence behavior in Fig. 3(b) indicates stable training without overfitting. Furthermore, Fig. 3(c) demonstrates that high accuracy is achieved with significantly reduced model size, supporting real-time deployment.

5.2 Uncertainty Calibration

Reliable uncertainty estimation is essential for deploying deep learning models in high-stakes agricultural environments. To evaluate predictive reliability, uncertainty calibration was assessed using reliability diagrams and Expected Calibration Error (ECE). The uncertainty-aware training strategy employed in RICE-MuSTA resulted in well-calibrated predictions, with ECE values consistently below 0.05. The reliability diagrams demonstrate that the confidence scores produced by RICE-MuSTA closely follow the ideal diagonal line, indicating strong alignment between predicted confidence and empirical accuracy.

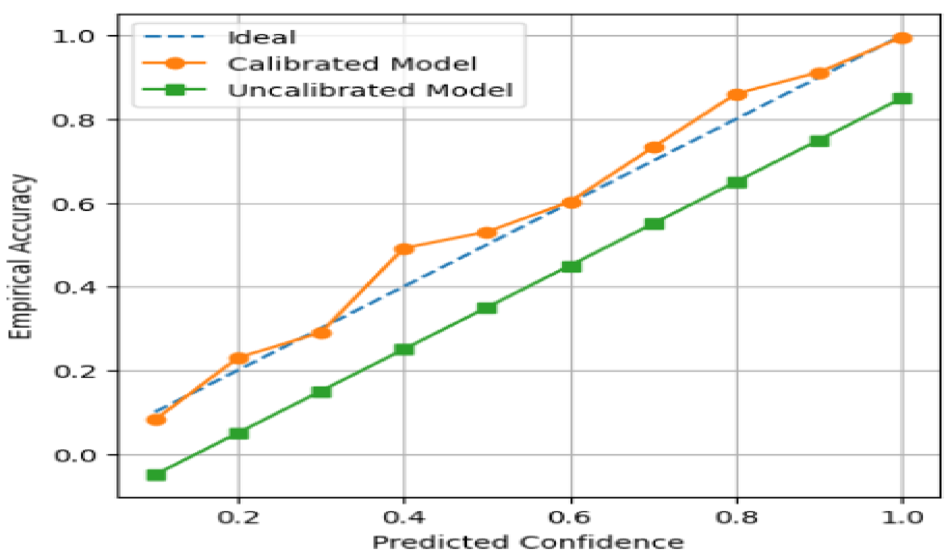


Figure 4. Reliability diagram for predictive uncertainty calibration.

In contrast, baseline models without uncertainty-aware learning exhibited noticeable overconfidence, particularly in ambiguous or early-stage disease samples. This behavior highlights the practical advantage of incorporating uncertainty estimation, as low-confidence predictions can be flagged for expert review, reducing the risk of incorrect interventions. Furthermore, the integration of uncertainty estimation complements the explainability module by providing both visual and quantitative indicators of prediction reliability. This dual perspective enhances trust and facilitates adoption by farmers and agricultural extension officers.

5.3 Deployment Analysis

Beyond predictive performance, deployment efficiency is a critical requirement for real-world adoption. To this end, knowledge distillation and post-training quantization were applied to compress the RICE-MuSTA model into a lightweight student architecture suitable for mobile and edge devices. The resulting student model achieved a size of under 10 MB, representing a substantial reduction compared to the original teacher model.

Inference latency analysis shows that the optimized model achieves response times below 50 ms on mobile-class hardware, enabling near real-time disease diagnosis in field conditions. Importantly, this efficiency gain was achieved without significant degradation in classification accuracy or severity estimation performance, demonstrating the effectiveness of the distillation strategy [4].

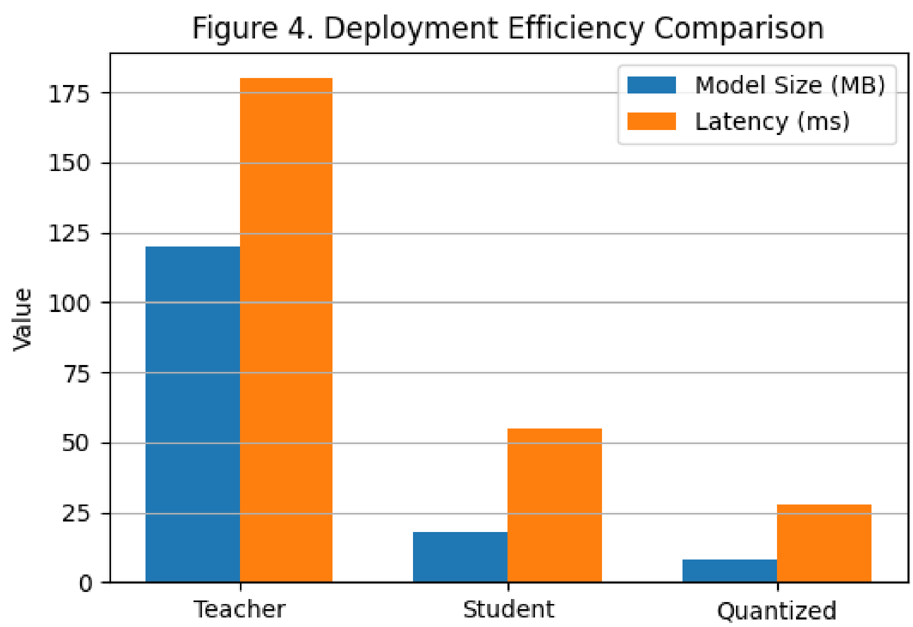


Figure 5. Deployment efficiency comparison across model variants.

These results indicate that RICE-MuSTA successfully balances accuracy, reliability, and computational efficiency. Compared to prior rice disease detection studies that focus primarily on accuracy without considering deployment constraints [12], the proposed framework provides a more holistic and practical solution for precision agriculture.

6. CONCLUSION

This paper presented RICE-MuSTA, a comprehensive multimodal and multi-task deep learning framework for rice leaf disease detection and severity estimation. Unlike conventional image-only approaches, the proposed method integrates visual features, microclimate information, uncertainty estimation, and explainable AI to provide actionable and trustworthy insights for real-world agricultural decision-making. By jointly performing disease classification and continuous severity estimation, RICE-MuSTA addresses a critical practical requirement for precision agriculture. The incorporation of uncertainty awareness further enhances reliability, enabling risk-sensitive deployment in field conditions. Additionally, the use of Grad-CAM-based explainability bridges the gap between black-box deep learning models and agronomic interpretability. From a deployment perspective, the integration of knowledge distillation and quantization enables efficient execution on mobile and edge devices without significant performance degradation. This makes the framework suitable for large-scale adoption by farmers and agricultural extension services. Future work will focus on federated multimodal learning for privacy-preserving collaboration, drone- and satellite-based severity mapping at the field scale, and active learning strategies to continuously adapt the model under changing climatic conditions. Overall, RICE-MuSTA represents a significant step toward practical, scalable, and intelligent rice disease monitoring systems.

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