Rice Varieties Classification in Bangladesh

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1 Related Work

Research on rice variety classification in Bangladesh spans both technological approaches using image analysis and machine learning, as well as socio-economic studies investigating farmers' adoption of modern rice varieties. The first stream focuses on computational methods for accurately identifying rice varieties, which is crucial for quality control, breeding programs, and market standardization.

Salman Qadri *et al.* (2021) proposed a machine vision-based approach using texture features for rice variety classification. They utilized a custom dataset comprising 10,800 grains from six varieties, captured with a smartphone camera under uncontrolled lighting conditions. Traditional machine learning models, including LMT, MCR, MB, T-J48, and MAS-C, were applied to classify the rice grains. The study reported high accuracy, with the LMT model achieving 97.4%. The approach demonstrated the feasibility of using interpretable machine learning techniques for small datasets and real-world images. However, the method was limited by the small size of the dataset, absence of deep learning techniques, and variability in lighting, which could affect generalization to other datasets or deployment in diverse conditions.

In contrast, Md. Masudul Islam *et al.* (2025) introduced a next-generation deep learning approach, combining Convolutional Neural Networks (CNNs) with Transformer-based attention mechanisms for rice variety classification. This study employed two datasets: a private dataset with 27,000 images across 20 classes and a public dataset with 6,750 images across 5 classes. The deep learning models achieved near-perfect accuracy, with 99.6% on the private dataset and 10% on the public dataset. Compared to traditional machine learning methods, this approach offers greater robustness, scalability, and suitability for real-world deployment. The main limitations include the need for high-performance GPUs for training, limited availability of public datasets, and few external validation studies to confirm generalizability. Collectively, these two studies illustrate the progression from conventional machine learning to deep learning methods in rice variety classification, highlighting improvements in accuracy, scalability, and model sophistication.

Beyond computational classification, research has also addressed factors influencing the adoption of modern rice varieties by farmers. Mohammad Samiul

Islam *et al.* (2024) conducted a survey of 510 Boro rice farmers in seven Upazilas of Mymensingh district. They collected detailed socio-economic, farm, and institutional data to understand drivers of adoption. Using a Tobit regression model, supported by descriptive statistics and chi-square analysis, the study identified education, farm size, access to extension services, training, credit, and seed availability as significant positive determinants. The model exhibited a strong fit, with Pseudo $R^2 = 0.8911$, indicating that it explained the majority of variance in adoption behavior. However, the study's scope was limited geographically to Mymensingh district, excluded other rice seasons (Aus and Aman), and relied on self-reported data, which may introduce bias.

Taken together, these studies provide a comprehensive view of rice variety research in Bangladesh. On the technological side, advancements in image-based classification—from traditional machine learning to CNN-Transformer models—have enhanced the accuracy and scalability of variety identification. On the socio-economic side, understanding the behavioral and institutional factors influencing farmers' adoption decisions is essential for effective dissemination of modern rice varieties and for designing policies that support sustainable agricultural practices. Future research could integrate these two perspectives, combining accurate automated classification systems with adoption studies to optimize rice production, distribution, and policy interventions in Bangladesh.

Table 1: Comparison of Rice Variety Classification Approaches

Title	**Dataset name and Link**	**Dataset description**	**Method name**	**Accuracy of the model**	**Pros**	**Cons**	**Citation**
Machine Vision Approach for Classification of Rice Varieties Using Texture Features	Custom dataset (captured via OPPO F3 camera, not public).	10,800 grains from 6 varieties (1,800 per variety). 512×512 grayscale; 3,600 ROI.	LMT, MCR, MB, T-J48, MAS-C.	**97.4% (LMT)**, 97.0% (MCR), 96.3% (MB), 95.74% (T-J48), 95.2% (MAS-C).	Real-world images; interpretable ML; efficient for small datasets.	Limited data; no deep learning; uncontrolled lighting.	Salman Qadri *et al., Int. J. Food Properties*, 2021. DOI: 10.1080/10942912.2021.1986523
Rice Variety Classification Using Next Generation Convolutional Networks	(1) Aruzz22.5K (private) (2) Cinar & Koklu (public).	27 k images (20 classes) + 6.75 k images (5 classes).	CNN + Transformer-based attention.	**99.6% (Dataset-01)**, **100% (Dataset-02)**.	High accuracy; robust; scalable; efficient for deployment.	Needs GPU; limited public data; few external tests.	Md. Masudul Islam *et al., J. Eng.*, 2025. DOI: 10.1049/tje2.70102
Factors Influencing Farmers' Behavior Towards Modern Rice Varieties in Bangladesh	Survey data (Mymensingh district, Bangladesh) — collected via structured questionnaire from **510 Boro rice farmers**.	Primary dataset from seven Upazilas: Phulpur, Fulbaria, Nandail, Trishal, Haluaghat, Gaffargaon, and Mymensingh Sadar. Includes socio-demographics, farm size, extension services, training, biophysical and institutional factors influencing rice variety adoption.	**Tobit Regression Model** (censored regression with ML estimation), supported by descriptive and chi-square analysis.	Model significant (Prob ¿ F = 0.000); **Pseudo R^2 = 0.8911**; 12 of 13 variables significant — key positive factors: education, farm size, extension contact, training, credit & seed access.	Comprehensive analysis; identifies key adoption determinants; useful for policy and extension strategy; high model fit.	Limited to Mymensingh district; excludes Aus and Aman seasons; self-reported data; lacks temporal validation.	Mohammad Samiul Islam *et al., Malaysian Journal of Agricultural Economics*, Vol. 31(1), 2024. DOI: 10.36877/mjae.a0000511