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RiceVision: A Cross-Platform System for Real-Time Rice Variety Identification Using Deep Learning

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Abstract: This study presents RiceVision, a cross-platform software system for real-time rice variety identification using deep learning–based image analysis. Unlike prior work that primarily focuses on classification accuracy, RiceVision emphasizes reproducibility, deployment, and usability in real-world agricultural environments. The system integrates a web-based platform and an offline-capable Android application within a unified architecture, ensuring consistent preprocessing and inference across platforms. Deep learning models are deployed using TensorFlow and TensorFlow Lite to support both online and on-device inference. The proposed hybrid framework combines convolutional neural networks (CNNs) and Vision Transformer (ViT) architectures using a stacked ensemble strategy. Experimental evaluation on a 62-class rice variety dataset demonstrated strong classification performance, where the stacked ensemble achieved an average 5-fold validation accuracy of 98.64%, outperforming individual VGG16 (90.64%) and ViT-B/16 (91.28%) models. The system further demonstrated stable convergence behavior and low inter-fold variance, indicating robust generalization capability. A centralized model management mechanism enables version control and seamless updates across deployment platforms. Detailed model configurations, validation results, and explainability analyses are provided in the Supplementary Material. RiceVision highlights the potential of deployable AI systems for practical decision support in digital agriculture.

Index Terms: Rice Variety Identification; Software Architecture; Web Application; Smart Agriculture

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1. Introduction

Rice cultivation supports the livelihoods of millions of farmers and plays a central role in food security and agricultural economies. Modern rice production systems depend heavily on genetically pure and correctly labeled seed, as varietal differences influence yield potential, stress tolerance, and grain quality traits. Accurate identification of rice varieties is fundamental to breeding programs, seed certification, quality assurance, and varietal authentication within agricultural supply chains [1]. In practice, these tasks often rely on expert visual inspection or laboratory-based analyses, which are time-consuming, subjective, and difficult to deploy in field or low-resource environments. Furthermore, real-world agricultural imaging conditions introduce substantial variability in illumination, background complexity, image noise, grain orientation, and camera quality, all of which can negatively affect classification reliability if not properly addressed during model development and deployment. As a result, varietal misidentification remains a persistent problem, leading to compromised seed purity, yield losses, and inefficiencies in certification and distribution workflows. Traditional rice variety identification methods initially relied on handcrafted morphological and texture-based image features combined with classical machine learning algorithms such as support vector machines (SVM), k-nearest neighbors (KNN), and decision trees. Early computer vision studies demonstrated that grain shape, color distribution, contour structure, and texture descriptors could effectively distinguish rice varieties under controlled imaging conditions [13]. These foundational approaches established the feasibility of automated rice classification and provided the basis for subsequent deep learning–based systems. With the advancement of convolutional neural networks (CNNs), feature extraction became increasingly data-driven and automated, significantly improving classification robustness and scalability [14]. More recently, transformer-based architectures [15] and ensemble learning methods have further enhanced recognition performance by capturing both local spatial characteristics and global contextual representations of rice grain morphology.

Recent studies have demonstrated that computer vision and machine learning techniques can achieve high accuracy in rice variety classification using grain images, including fuzzy systems [5], convolutional neural networks [6-8], quantized neural networks [9], ensemble learning approaches [10], and next-generation deep architectures [11]. While these methods show promising performance under experimental conditions, most studies emphasize algorithmic accuracy rather than system deployment, reproducibility, or end-user accessibility. Consequently, few solutions are available as usable tools for breeders, extension workers, or quality-control personnel in real-world agricultural settings. This application note presents RiceVision, a cross-platform software system designed to bridge this gap by translating deep-learning–based rice variety classification into a deployable and reproducible application. RiceVision integrates an open-source web-based app (https://github.com/abrahametry/Rice_Prediction_Web) and an offline-capable Android mobile application (https://github.com/abrahametry/rice_prediction_flutter) within a unified architecture, enabling consistent real-time inference across platforms and supporting practical use in both laboratory and field environments. The underlying deep-learning models and experimental analyses that form the basis of RiceVision have been previously reported by the authors [12], while the present application note focuses on software architecture, deployment, and real-world usability.

While previous studies have demonstrated high classification accuracy using deep learning models, limited attention has been given to reproducible deployment and user-accessible tools. This work addresses that gap by presenting a complete software system, with implementation details, validation protocols, and supplementary technical documentation provided for reproducibility.

A potential challenge in AI-based rice classification systems is the variability of rice morphology across geographic regions, cultivation environments, and breeding practices. Since grain appearance characteristics such as shape, texture, transparency, and chalkiness may differ substantially among regional rice varieties, models trained on geographically localized datasets may exhibit reduced performance when directly applied to unseen international cultivars. Therefore, beyond classification accuracy, scalable deployment frameworks must support adaptability to region-specific datasets and continuously evolving varietal distributions. RiceVision was designed with this consideration in mind by separating application logic from model architecture, enabling retraining and deployment of customized models for different agricultural contexts without requiring modifications to the software infrastructure.

2. Web and Mobile App Development

2.1. System architecture

RiceVision is designed as a modular, cross-platform software system that enables consistent rice variety identification across web and mobile environments. The architecture follows a service-oriented design in which image preprocessing, model inference, and result visualization are standardized and decoupled from platform-specific implementation details. This design ensures reproducibility, scalability, and ease of maintenance while supporting both online and offline usage scenarios.

The system consists of two primary deployment pathways: a web-based application for browser-based inference and an Android mobile application for on-device classification. Both platforms implement the same image

preprocessing logic and inference workflow to guarantee consistency of predictions across environments. Deep-learning models trained using TensorFlow/Keras are deployed on the web backend, while their optimized TensorFlow Lite counterparts are embedded within the mobile application to enable fully offline inference. A centralized model management mechanism maintains versioning, metadata, and compatibility between web and mobile models, preventing discrepancies during deployment or updates. Fig. 1 illustrates the overall architecture and deployment pipelines of our RiceVision Web and Mobile App system.

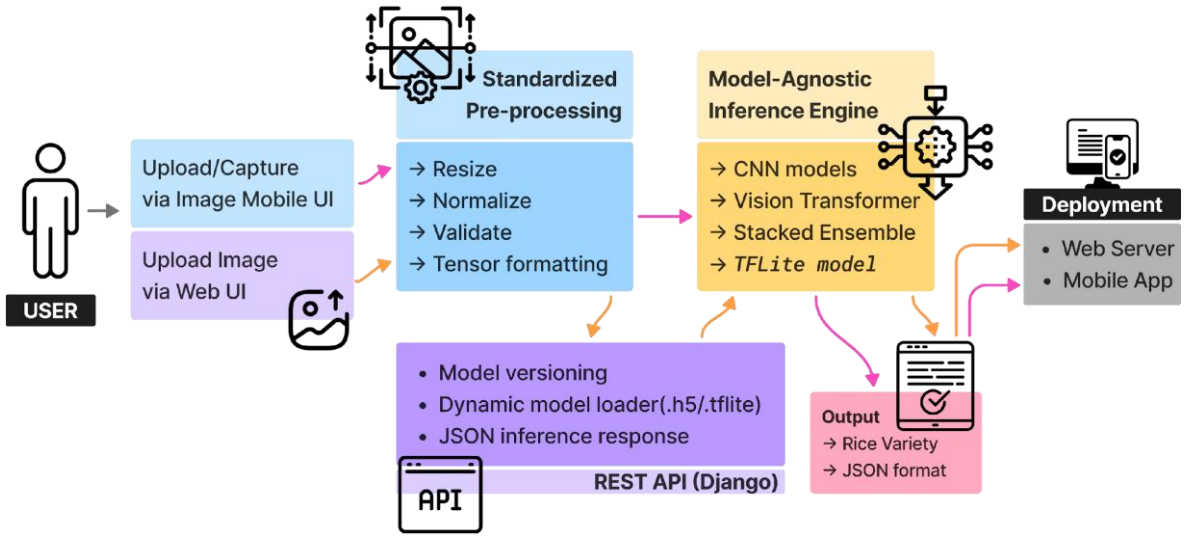


Fig. 1. Modular system architecture of the rice variety classification framework, showing user interaction via web and mobile interfaces, standardized preprocessing, model-agnostic inference engine with CNN, Vision Transformer, and stacked ensemble models, REST API management, and deployment across web and mobile platforms with JSON-based output.

Fig. 2 is the proposed system architecture presents an end-to-end pipeline for rice variety classification, integrating both web and mobile platforms with a hybrid deep learning backend. Users capture or upload rice grain images through either a web application or an Android mobile app. The input image undergoes backend preprocessing, including resizing and normalization, to ensure consistency across inputs. The processed image is then fed into two parallel feature extraction models: a Convolutional Neural Network (CNN) and a Vision Transformer (ViT). These models independently learn spatial and contextual features, and their outputs are combined using a stacked ensemble strategy to improve classification robustness and accuracy. The predicted class label is returned to the interface for display. On the web platform, results are additionally stored in a structured JSON format with validation checks for data consistency. For mobile deployment, the trained ensemble model is converted into a TensorFlow Lite (TFLite) format, enabling lightweight, on-device inference without relying on continuous server communication. This unified architecture ensures scalability, cross-platform usability, and efficient real-time prediction for practical agricultural applications.

2.2. Software components

RiceVision is composed of four main functional components that together form an end-to-end rice variety identification pipeline.

(1) Image ingestion and preprocessing module: Images can be uploaded through the web interface or captured directly using the mobile application. All images pass through a unified preprocessing pipeline that performs format validation, resizing to a fixed resolution (224 × 224 pixels), RGB normalization, and tensor conversion. This identical preprocessing logic is implemented in both the Django-based backend and the Flutter mobile client to ensure platform-independent inference behaviour.

(2) Model-agnostic inference engine: The inference engine is designed to be independent of specific deep-learning architectures. On the web platform, trained TensorFlow/Keras models are dynamically loaded and executed, while on mobile devices, a quantized TensorFlow Lite model performs on-device inference. The engine standardizes prediction outputs by returning the predicted rice variety along with confidence scores and model-version metadata, enabling transparent and reproducible results. This design allows new models to be integrated without modifying application-level code.

(3) Web backend and administration interface: The web application is implemented using the Django framework and exposes REST-based endpoints for image upload, prediction, and result retrieval. An administrative dashboard allows authorized users to manage model files, update rice variety metadata, and track model versions. Model integrity is preserved through version control and checksum validation, supporting reproducible deployment across environments.

(4) Mobile application with offline inference: The Android application, developed using Flutter, embeds a pretrained TensorFlow Lite model that enables real-time rice variety identification without requiring internet connectivity. Users can capture or select images, perform instant inference on-device, and view prediction results with confidence scores. Optional local caching allows recent predictions to be reviewed later, supporting field-level use where connectivity is limited or unavailable.

2.3 Model Design and Validation Overview

The RiceVision classification backend is designed as a hybrid deep learning framework that integrates convolutional neural networks (CNNs) and Vision Transformer (ViT) architectures within a stacked ensemble strategy to enhance predictive robustness and generalization. Transfer learning is employed using ImageNet-pretrained weights, enabling efficient feature extraction from rice grain images while reducing training complexity. The input images are standardized to a fixed resolution (224 × 224 RGB) and processed through parallel feature extraction pipelines, where spatial features are captured by CNN backbones and global contextual representations are learned by the ViT model. The outputs from these models are subsequently combined using an ensemble learning approach to produce the final classification. Model optimization follows a two-stage training strategy, including initial training of classification heads followed by partial fine-tuning of backbone layers. Regularization techniques such as dropout, L2 weight decay, and label smoothing are incorporated to mitigate overfitting, while adaptive optimization methods (Adam/AdamW with cosine decay scheduling) are used to ensure stable convergence. To improve robustness under real-world imaging conditions, the training pipeline incorporated multiple augmentation and normalization strategies designed to simulate practical environmental variability. During training, input images were subjected to random rotations, brightness and contrast adjustments, horizontal and vertical flipping, zoom transformations, and minor noise perturbations to improve invariance against grain orientation, illumination changes, sensor noise, and capture inconsistencies. The preprocessing pipeline further standardized image dimensions and RGB normalization across both web and mobile platforms to reduce domain discrepancies arising from different acquisition devices and deployment environments. These measures improved the model's ability to generalize under varying lighting conditions, heterogeneous backgrounds, and mobile camera inputs commonly encountered in field-level agricultural applications. Detailed hyperparameter configurations and training settings are provided in Table 1 and Table 2. The performance of the proposed framework is evaluated using standard classification metrics, including accuracy and loss, along with robustness assessment through 5-fold

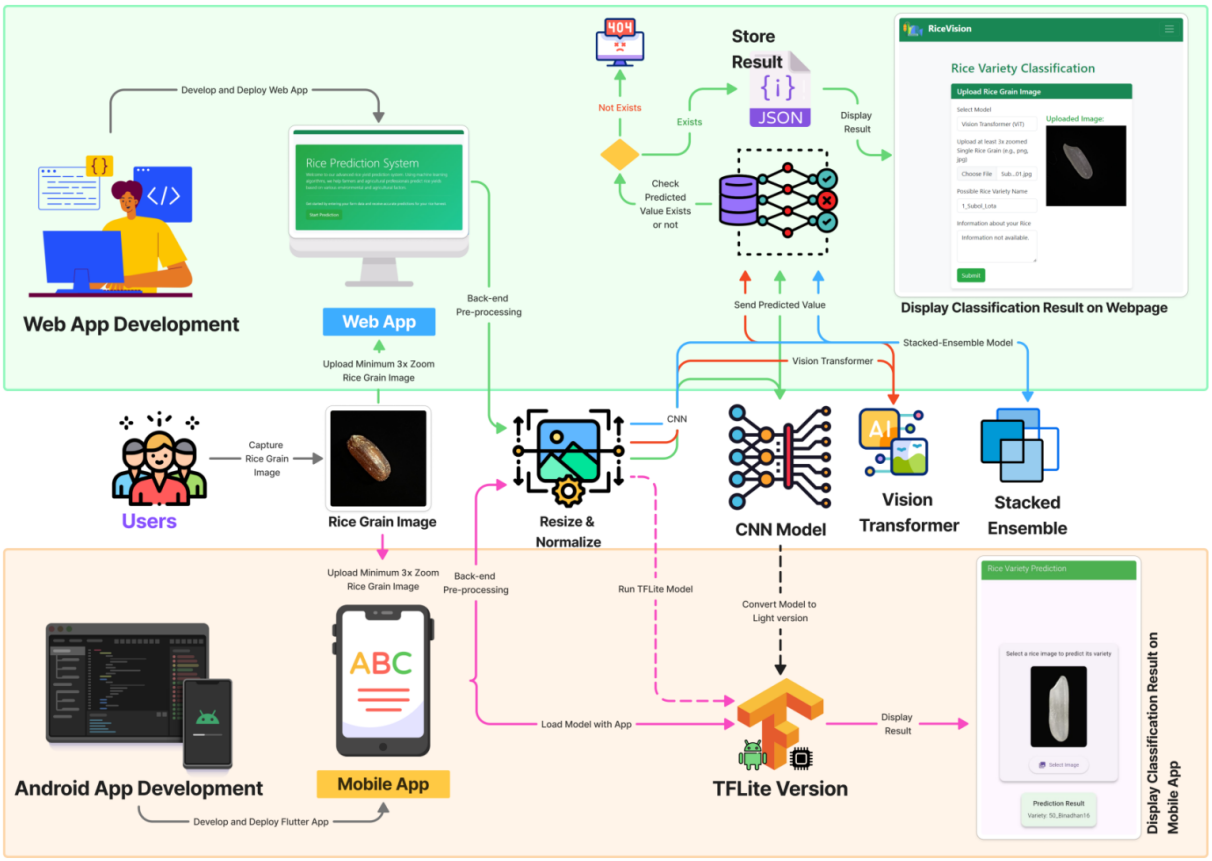


Fig. 2. Overall system architecture of the proposed rice variety classification framework, illustrating data acquisition from users via web and mobile applications, preprocessing, hybrid CNN–Vision Transformer stacked ensemble model, result storage, and deployment using TensorFlow Lite for real-time mobile inference.

cross-validation. Experimental results demonstrate that the stacked ensemble consistently outperforms individual models, achieving high validation accuracy with low variance across folds. Training dynamics and convergence behavior are illustrated through accuracy and loss curves, while cross-validation results confirm stable generalization. These detailed evaluation results are presented in Supplementary Fig. 3, Fig. 4, Fig. 5.

Table 1. Optimized Hyperparameter Settings for Transfer-Learning Models.

Parameter	Setting
Image Size	224 × 224 (RGB)
Batch Size (per replica)	16 (scaled to global batch = 16 × replicas)
Backbones Tested	MobileNetV2, VGG16, InceptionV3, Xception
Pretraining	ImageNet weights (transfer learning)
Head Layers	GAP → Dropout(0.30) → Dense(256, ReLU, L2=1e-4) → BatchNorm → Dense(62, Softmax)
Dropout Rate	0.3
Regularization	L2 = 1e-4 (applied to Dense layer)
Loss Function	Categorical Cross-Entropy with Label Smoothing = 0.05
Optimizer (Stage 1)	Adam, Learning Rate = 3×10^{-4}
Optimizer (Stage 2)	Adam + Cosine Decay (initial LR = 1×10^{-4}, $\alpha = 0.1$)
Training Stages	Stage 1: Train head only (8 epochs) Stage 2: Fine-tune top 40% backbone (25 epochs)
Unfreezing Policy	Top 40% of backbone layers unfrozen in Stage 2
Callbacks	EarlyStopping (patience=8, monitor=val_acc) ReduceLROnPlateau (patience=3, factor=0.2, min_lr=1e-6) ModelCheckpoint (weights only, best val_acc)
Precision Policy	Mixed Precision (bfloat16, logits in float32 for stability)

Table 2. Optimized Hyper-parameter Settings for Google's ViT-B/16 models.

Parameter	Google's ViT-b/16 Implementation
Image Size	224 × 224
Patch Size	16
Batch Size	32
Number of Classes	62
Epochs	30
Learning Rate (LR)	0.0001 (AdamW)
Weight Decay	0.1
Optimizer	AdamW + CosineAnnealingLR
Dropout Rate	0.3
Projection/Embed Dim	1024
MLP Hidden Dim	512
Attention Heads	16
Transformer Layers	12
Regularization	AdamW weight decay
Early Stopping	Not Applied
Scheduler	CosineAnnealingLR

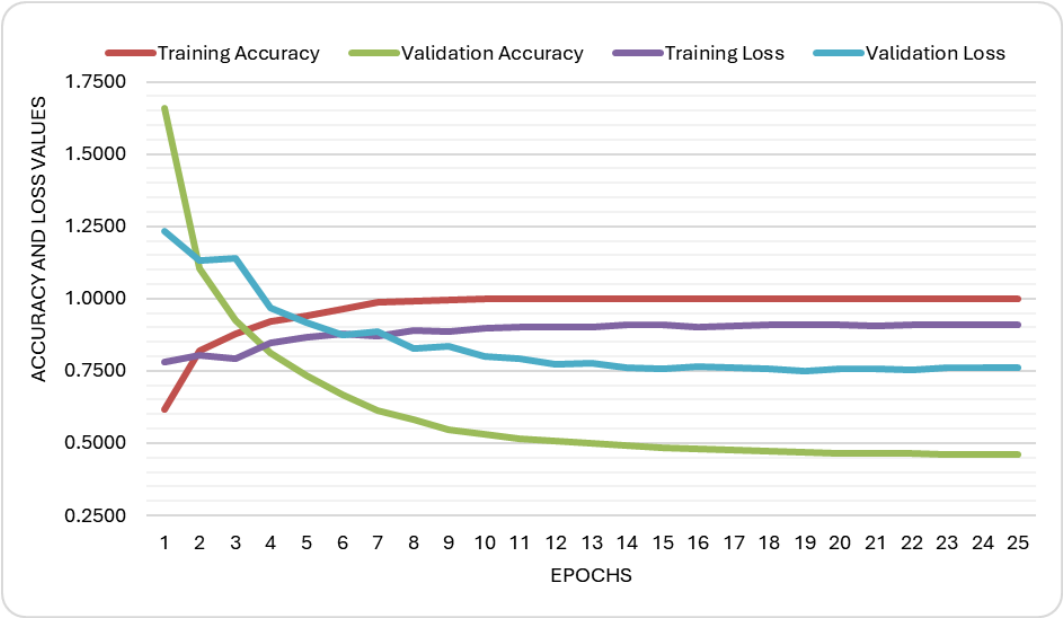


Fig. 3. Training and Testing Accuracy and Loss Curves of the Best-Performing CNN Model (VGG16).

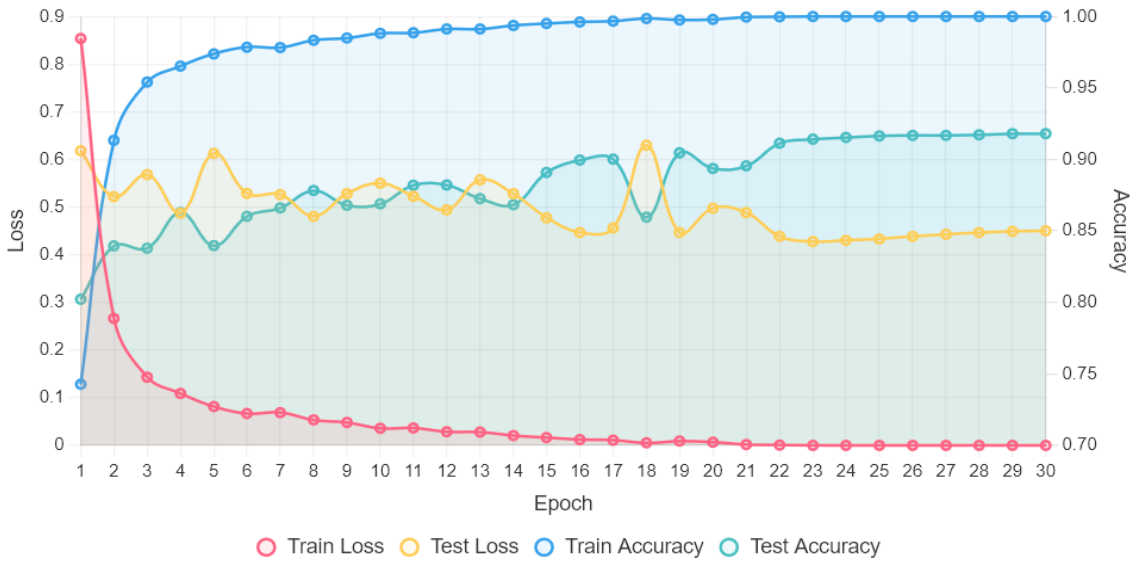


Fig. 4. Training and Testing Accuracy and Loss Curves of Google's ViT-B/16 model.

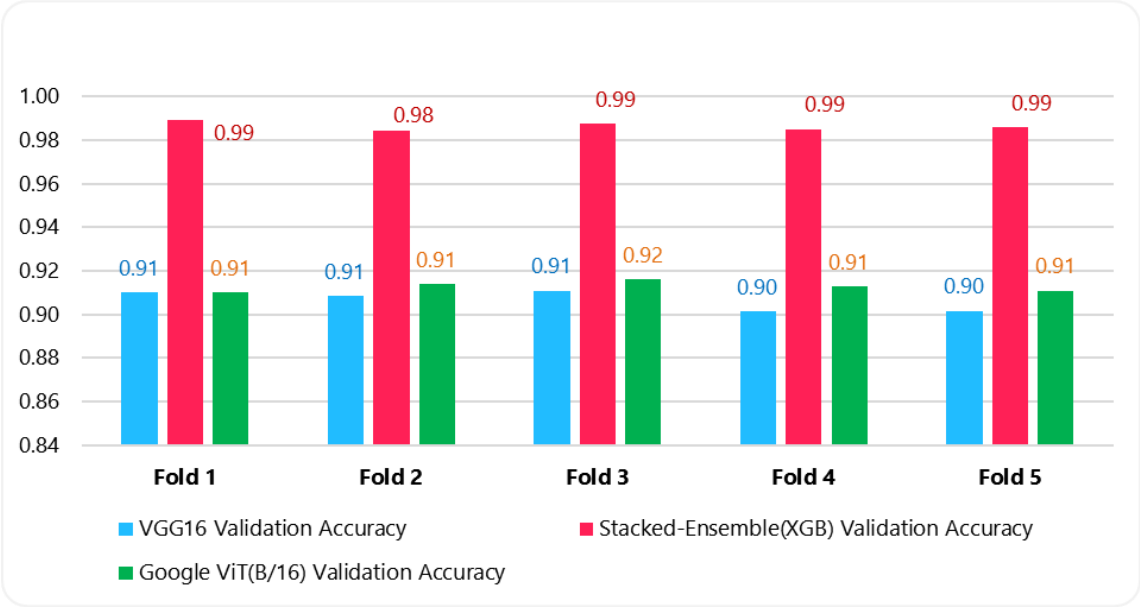


Fig. 5. Robustness analysis showing consistent 5-fold validation accuracy for VGG16, stacked-ensemble (XGBoost), and Google ViT-B/16, demonstrating stable generalization across all folds.

2.4. Application and Use Cases

RiceVision is designed for the practical identification of rice varieties in both laboratory and field environments. The web and mobile applications enable users to upload rice-grain images through a browser interface and receive instant classification results, including the predicted variety name across 62 supported rice varieties at present [2-4] which is represented with detailed morphological characteristics summarized in Supplementary Table A1. This mode is suitable for research laboratories, seed testing facilities, and institutional workflows where internet connectivity is available and centralized model management is required. For field-level deployment, RiceVision provides an Android mobile application (https://appetize.io/app/b_gwfq3qfr6ojdsgt77chdxw44ae) that supports fully offline inference using an embedded TensorFlow Lite model. Users can capture images directly with a smartphone camera or select images from local storage, after which the application performs on-device pre-processing and inference without requiring network access. An administrative interface allows authorized users to update rice variety names, associated descriptions, and deployed computer vision models, supporting flexible system maintenance and adaptation. The overall user and administrator interaction workflow of the RiceVision system is illustrated in Fig. 6.

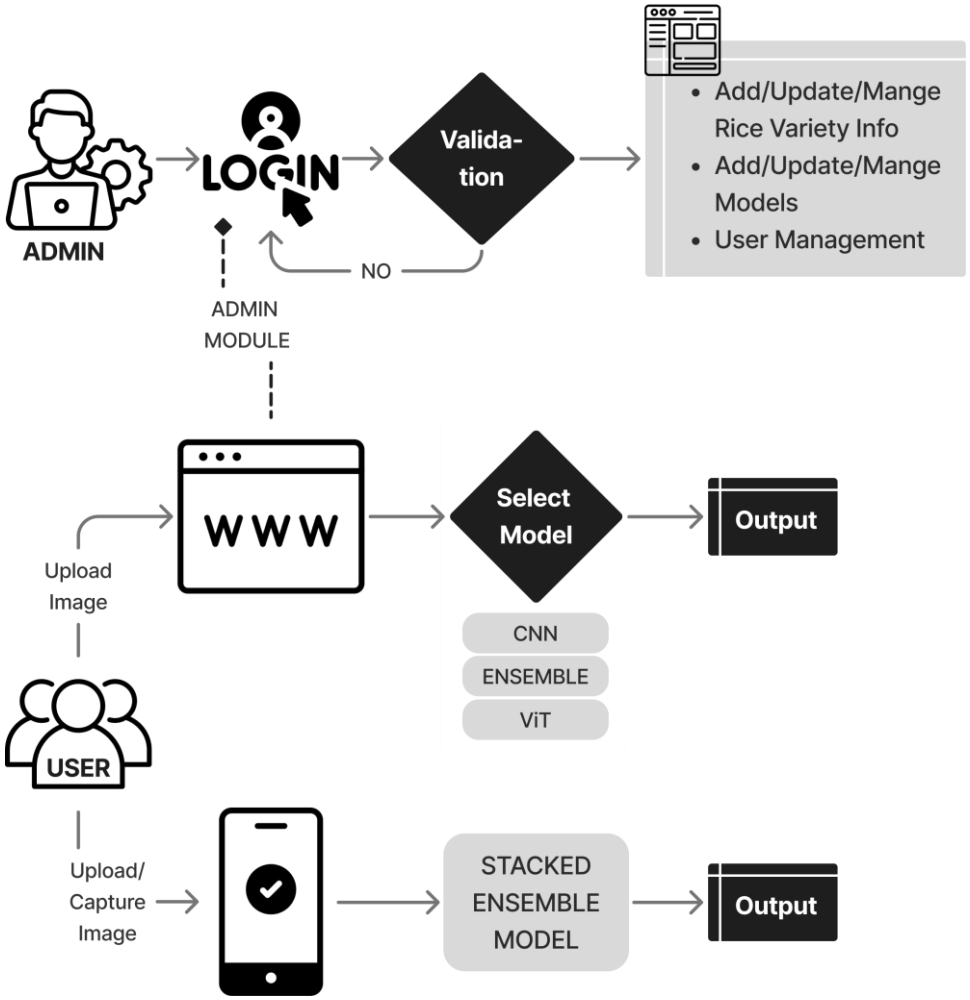


Fig. 6. User and Admin workflow for RiceVision system.

To demonstrate the operation and usability of RiceVision, illustrative examples from both the web and mobile interfaces are presented in Fig. 7. These examples show how users interact with the system for image upload, model selection, inference, and visualization of classification results. While the current pre-deployed model is trained on a comprehensive dataset of 62 distinct rice varieties primarily cultivated in Bangladesh and South Asia, the RiceVision architecture is inherently region-agnostic. While the currently deployed pretrained model was trained primarily on 62 rice varieties cultivated in Bangladesh and neighboring South Asian regions, the RiceVision framework was intentionally designed as a region-adaptive system rather than a geographically fixed classifier. Rice grain morphology varies considerably across global agricultural ecosystems due to differences in genetics, climate, cultivation practices, and post-harvest processing. Consequently, direct generalization to all international rice varieties cannot yet be fully guaranteed without additional cross-regional validation. To address this limitation, RiceVision decouples model implementation from application-layer functionality, allowing researchers, breeders, and agricultural organizations to integrate newly trained regional models through the administrative interface without modifying the underlying source code. The framework supports deployment of custom TensorFlow and TensorFlow Lite models adapted to local varietal distributions, thereby enabling scalable international extensibility and future global validation studies. Rice morphology varies significantly across global climatic zones; therefore, the system was designed to decouple the model from application logic. Through the administrative interface, international researchers and extension agencies can upload custom-trained models (in .h5 or .tflite formats) adapted to local varietal characteristics without requiring modifications to the source code. This design enables RiceVision to function as a globally adaptable tool for rice variety identification in diverse agricultural contexts.

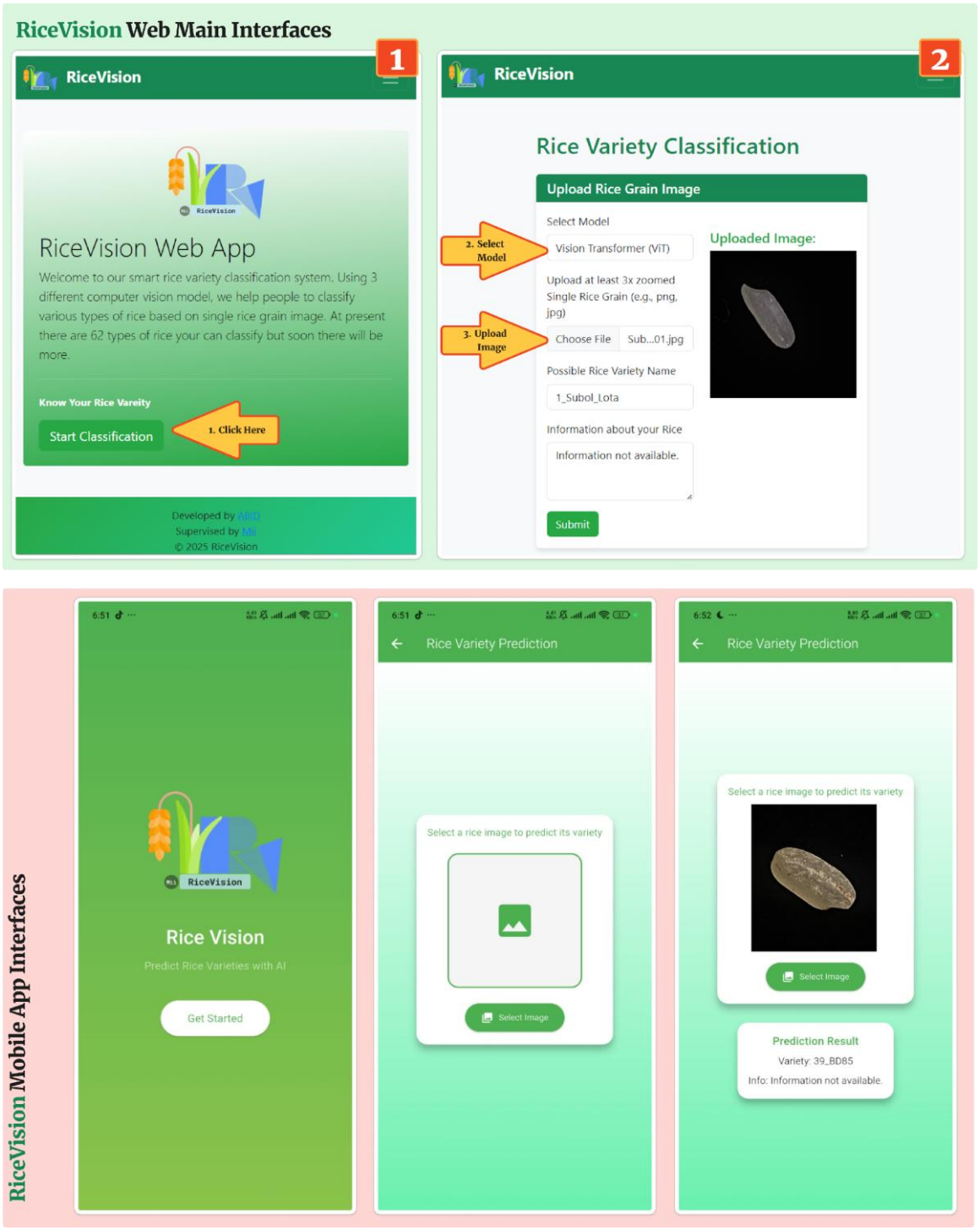


Fig. 7. RiceVision Web and Mobile App User Interfaces.

3. Significance of the Application

The significance of RiceVision for the digitalization of rice production lies in its ability to operationalize deep learning–based rice variety identification within practical agricultural workflows. Although image-based classification models have demonstrated strong performance in research settings, their integration into everyday agricultural practice has remained limited due to challenges related to usability, deployment complexity, and accessibility. RiceVision addresses these challenges by providing an application-oriented solution that enables agricultural stakeholders to benefit from advanced image analysis without requiring specialized technical expertise. A key contribution of the application is its support for both web-based and mobile deployment, allowing rice variety identification to be conducted across laboratory, institutional, and field environments. The availability of fully offline inference on mobile devices is particularly valuable in rice-growing regions where internet connectivity is unreliable or unavailable, thereby enhancing

the practicality of digital tools in real-world agricultural contexts. By ensuring consistent predictions through a unified preprocessing and inference pipeline and supporting centralized model management, RiceVision contributes to reliable and scalable digital workflows in rice production. Overall, the application demonstrates how deep learning–based image analysis can support the digitalization of rice production by enhancing varietal authentication, improving decision-making, and strengthening seed quality management processes.

4. Validation and Reproducibility

The reliability of RiceVision is established through systematic evaluation and deployment-aware validation. Model performance was assessed using accuracy and loss metrics, complemented by 5-fold cross-validation to examine generalization stability. The stacked ensemble consistently achieved high validation accuracy with low inter-fold variance, indicating robust performance beyond single-split evaluation. Detailed training dynamics and cross-validation outcomes are provided in Supplementary Fig.1, Fig. 2, and Fig. 3. To support interpretability, model explainability techniques were applied, revealing that predictions are driven by discriminative morphological features of rice grains rather than spurious patterns. Representative visualizations are shown in Fig. 8. Reproducibility is ensured through a unified preprocessing pipeline, consistent inference logic across web and mobile platforms, and controlled model versioning. Comprehensive training configurations and hyperparameter settings are documented in Table 1 and Table 2, enabling independent verification. From a practical standpoint, RiceVision translates validated deep learning models into a deployable tool that maintains consistency across environments. Its support for both server-based and on-device inference enables reliable operation under varying connectivity conditions, making it suitable for real-world agricultural workflows such as seed verification and varietal authentication.

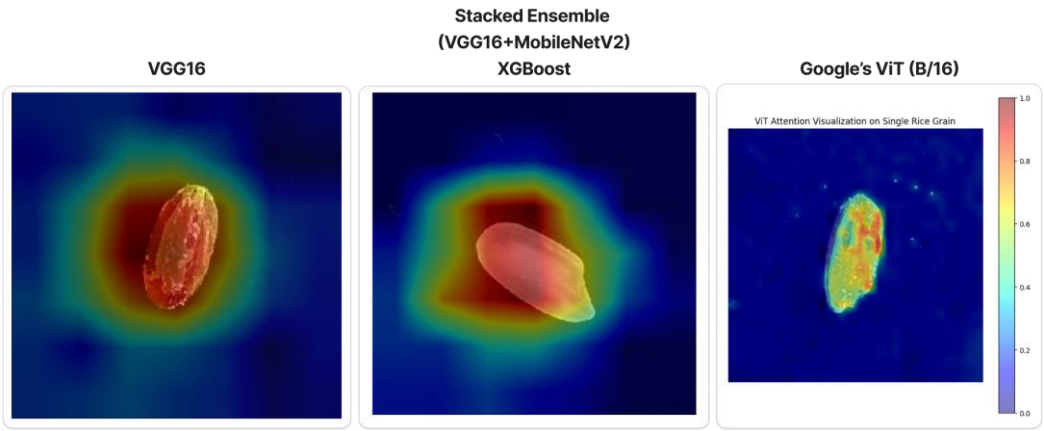


Fig. 8. Explainability visualizations for rice kernel classification using three model types.

5. Availability and Implementation

RiceVision is implemented as a cross-platform system comprising a Django-based web application and a Flutter-based Android mobile app with offline inference using TensorFlow Lite. The source code is publicly available via GitHub (**web:** https://github.com/abrahametry/Rice_Prediction_Web**; mobile:** https://github.com/abrahametry/rice_prediction_flutter), with an online demo accessible at https://appetize.io/app/b_gwfq3qfr6ojdsgt77chdxw44ae. The system ensures consistent preprocessing and inference across platforms, with centralized model versioning for reproducibility. Detailed model configurations and validation results are provided in the Supplementary Material.

6. Conclusions

This application note introduced RiceVision, a cross-platform application for real-time rice variety identification using deep learning and grain image analysis. By supporting both online and offline operations and ensuring consistent preprocessing and inference across platforms, RiceVision addresses key challenges related to usability and deployment in real agricultural environments. The application demonstrates how deep learning models can be operationalized as a practical decision-support tool for rice production and seed quality management. Although the current implementation demonstrates strong performance on a large South Asian rice variety dataset, broader international evaluation across geographically diverse rice cultivars and imaging conditions remains an important direction for future research. Future work will therefore focus on multi-regional dataset integration, domain adaptation strategies, and cross-country validation to further improve global generalization capability. Future work will focus on expanding varietal coverage,

improving interpretability, and facilitating adaptation to region-specific datasets to further support the digitalization of rice production.

All the Declarations and Statements

Author Contributions Statement

Al Hossain Abid – Developed proposed system, Software Implementation: Handled data acquisition, dataset preprocessing, and implementing the research model.
Mirza Niaz Morshed – Contributed to Literature Study, Review and Editing
Md. Ashif-Ul-Haque – supervised project execution
Md. Masudul Islam – Conceptualization, Methodology, and Supervision: Proposed research ideas, Constructed the overall framework, and supervised project execution, Model Training, Validation, and Performance Evaluation: Led the model training process, validated results using standard metrics, and benchmarked performance against existing methods, Drafted the initial manuscript, contributed to the literature survey, and documented the technical background of the study.
Md. Shafiqul Islam – Review and Editing, and Project Management: Reviewed and edited the manuscript, ensured clarity and coherence, and helped coordinate project milestones and deadlines.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

No Funding.

Data Availability Statement

The dataset is publicly available in following link: https://www.kaggle.com/datasets/abrahametry/rice-62-varieties-dataset

Ethical Declarations

This study used only publicly available, anonymized datasets. No human subjects were directly involved in the experimental research, and no ethical approval was required beyond standard institutional guidelines for secondary data use.

Acknowledgments

Not Applicable.

Declaration of Generative AI in Scholarly Writing

AI-assisted technologies are used for basic language and grammar check.

Abbreviations

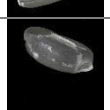
The following abbreviations are used in this manuscript:

AI - Artificial Intelligence
DL - Deep Learning

Appendix A: Dataset Description

Table A1. Visual Feature Comparison of All Rice Varieties

Variety	Image	Shape	Tip Morphology	Surface Texture	Color / Transparency	Distinctive Visual Notes
AMON		Medium–short	Slight hook	Patchy + chalk spots	Semi-opaque	Brownish spots on surface
ARBORIO		Short, round	Blunt	Very smooth	White, highly opaque	Classic plump Arborio type

BASHFUL		Short	Rounded	Smooth	Light translucent	Slight belly curvature
BD30		Long	Tapered	Mild striations	Translucent	Smooth dorsal line
BD33		Long	Tapered	Smooth	Semi-translucent	Visible center chalk band
BD39		Long	Rounded tip	Mildly chalky	Semi-translucent	Wispy chalk traces
BD49		Long	Sharp	Striated	Semi-opaque	Greyish tint, dorsal ridge
BD51		Long	Sharp	Rough patches	Semi-translucent	Broad dorsal chalk line
BD52		Long	Sharp	Rough	Semi-opaque	Dense white patch at center
BD56		Long	Slight taper	Smooth	Grey-translucent	Mild stripe marks
BD57		Long	Sharp	Smooth	Translucent	Faint vertical groove
BD70		Long	Sharp	Smooth	Slightly opaque	White embryo spot
BD72		Long	Narrow tip	Patchy	Greyish	Multiple chalk spots
BD75		Long	Sharp	Striated	Semi-opaque	Scattered chalk pits
BD76		Long	Tapered	Rough	Opaque	Heavy chalk regions
BD79		Long	Sharp	Rough	Semi-translucent	Pale greenish hue
BD85		Long	Ridge-sharp	Smooth	Semi-translucent	Wrinkled appearance
BD87		Medium	Blunt	Smooth	Semi-translucent	Slight dorsal crease
BD91		Medium–long	Tapered	Smooth	Light opaque	Soft chalk patches
BD93		Long	Rounded	Smooth	Semi-opaque	Greyish tone
BD95		Long	Tapered	Smooth	Light opaque	Mild belly chalk

BINADHAN07		Long	Sharp	Smooth	Opaque	Subtle chalk bands
BINADHAN08		Long	Sharp	Rough	Semi-translucent	Oval chalk mark at center
BINADHAN10		Long	Tapered	Smooth	Opaque-white	Strong dorsal chalk stripe
BINADHAN11		Long	Sharp	Smooth	Translucent	Fine vertical grain pattern
BINADHAN12		Long	Slight hook	Pitted	Semi-opaque	Large chalk blotch area
BINADHAN14		Long	Sharp	Smooth	Semi-translucent	Thin, slender body
BINADHAN16		Long	Hooked	Smooth	Semi-opaque	Slight embryo dent
BINADHAN17		Long	Sharp	Striated	Opaque	Deep dorsal crease
BINADHAN19		Long	Very slender	Smooth	Translucent	Needle-like shape
BINADHAN21		Long	Sharp	Smooth	Semi-translucent	Uniform matte texture
BINADHAN23		Medium	Blunt	Slightly chalky	Semi-opaque	Roundish belly
BINADHAN24		Medium–long	Tapered	Smooth	Semi-translucent	Light tip chalk
BINADHAN25		Long	Sharp	Rough	Semi-translucent	Dense chalk clusters
BINADHAN26		Long	Rounded	Smooth	Semi-opaque	Soft surface marks
BR22		Long	Sharp	Smooth	Semi-translucent	Very clear dorsal ridge
BR23		Long	Sharp	Smooth	Slightly opaque	Tip has chalk bloom
BR28		Medium	Blunt	Smooth	Semi-translucent	Curved belly
BR29		Medium–long	Blunt-taper	Smooth	Semi-translucent	Mild chalk belly
BRRI67		Long	Sharp	Smooth	Semi-transparent	Dense center chalk

BRRI74		Long	Wide-belly	Smooth	Greyish	Round embryo pit
BRRI102		Long	Sharp	Smooth	Semi-opaque	Long dorsal chalk streak
CHINIGURA POLAO		Short	Round	Smooth	White opaque	Small classic aromatic grain
DESHI BASHMOTI		Medium-long	Sharp	Smooth	Light opaque	Slight aromatic-type curvature
GANJIYA		Very short	Blunt	Brown husk	Bran-colored	Only variety with full bran visible
GUTISHORNA		Medium	Blunt	Patchy	Semi-opaque	Large chalk + husk remnants
IPSALA		Long	Sharp	Smooth	Translucent	Turkish type, very slender
JASMINE		Medium-short	Blunt	Smooth	White opaque	Classic jasmine appearance
JIRASHAIL		Medium	Tapered	Smooth	Semi-opaque	Slight chalk lines
KARACADAG		Long	Blunt	Patchy	Opaque	White thick chalk layer
KATARI POLAO		Short–medium	Tapered	Smooth	Light translucent	Soft chalk belly
KATARIVOG		Medium	Tapered	Smooth	Semi-translucent	Very slender tip
LALAUSH		Short	Blunt	Rough	Brownish	Deep bran remnants
LALBINNI		Short	Blunt	Rough	Red-brown	Fully bran colored
LALBIROI		Medium	Tapered	Rough	Brown-white mixed	Partial bran + chalk
NAZIRSHAIL		Long slender	Sharp	Smooth	Semi-opaque	Popular aromatic type silhouette
PAIJAM		Medium	Blunt	Smooth	Semi-transparent	Roundish tip
REDCARGO		Short	Blunt	Rough	Deep red	Distinct cargo-rice trait
SHOMPA KATARI		Medium	Tapered	Smooth	Semi-translucent	Thin upper half

SHORNA5		Medium–long	Sharp	Smooth	Light translucent	Rounded belly
SUBOLLOTA		Medium-long	Tapered	Smooth	Semi-opaque	Slight curved spine
TURKISH BASMATI		Long slender	Very sharp	Smooth	Translucent-white	Very basmati-like needle grain

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