RESEARCH PAPER

Quality-Focused Classification Of Rice Seed Variety And Age Using Attention-Fused Recurrent Integration

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Abstract

Evaluating the quality of rice seeds is vital for crop productivity, particularly in the face of changing climatic conditions and increasing food demand. Existing rice-seed classification methods either rely on complex imaging systems, handcrafted features, or lack the ability to perform both variety and age classification simultaneously. Hence, this study aims to develop a unified, deep learning-based approach that accurately classifies rice-seed varieties and age using accessible RGB imagery, for which this work proposed RiceNet-AFRI (Rice Network Attention-Fused Recurrent Integration), a spatial-temporal deep neural network trained on an open-access dataset of three rice varieties—Akitakomachi, Yandao-8, and Koshihikari. The model achieved 98.25% accuracy in variety classification and 85.9% in age classification, outperforming traditional ML methods and closely matching or exceeding state-of-the-art deep learning benchmarks. RiceNet-AFRI is the first RGB-based deep learning model to offer simultaneous classification of rice-seed variety and age using an open dataset. RiceNet-AFRI offers a robust and scalable solution for rice-seed quality evaluation, with potential for future extensions into seed viability prediction.

Keywords: Rice seed classification, deep learning, spatial-temporal features, seed age prediction, RGB imaging, agricultural AI

How to cite this article: Hassan BN, Somashekara MT. Quality-Focused Classification of Rice Seed Variety and Age Using Attention-Fused Recurrent Integration. Int J Drug Deliv Technol. 2026;16(12s): 1011-1025. DOI: 10.25258/ijddt.16.12s.113

1 Introduction

Rice, a staple food for over half of the world's population, begins its journey from a humble seed. The rice seed serves as the fundamental unit of rice cultivation, encapsulating the genetic potential necessary for developing a productive plant capable of delivering high yields [1]. The quality of these seeds is crucial; it determines not only crop productivity but also resilience against diseases and environmental fluctuations. High-quality seeds contribute to uniform crop stands, improved resistance to pests and diseases, and better adaptability to climate changes [2]. In regions like Asia, where rice is a dietary staple and cultural cornerstone, seed quality directly impacts food security and socio-economic stability [3]. The role of seeds extends beyond agriculture, they are the starting point of sustainable farming practices, enabling farmers to enhance yield potential while reducing dependence on agrochemical inputs [4]. Rice consumption is especially concentrated in Asia, accounting for approximately 90% of the global demand [5]. Countries such as India, China, Indonesia, and Bangladesh are among the largest consumers [6]. However, rice is not confined to the Asian palate; it is widely consumed across Africa, Latin America, and parts of the Middle East, showcasing its global importance and versatility in culinary practices [7].

Despite its global significance, rice-seed classification and quality evaluation remain underexplored in modern computational agriculture. Traditional methods rely heavily on manual inspection, which is time-consuming, error-prone, and lacks scalability [8], [9]. One of the primary challenges in automating rice-seed classification is the limited availability of labeled datasets, especially those that include both variety and age-related annotations [10]-[20]. Most existing datasets are either small in scale or lack age differentiation, hindering development of robust models for longitudinal seed analysis. Another significant limitation in existing approaches is the absence of advanced feature extraction techniques. Many models focus solely on raw image data or basic statistical descriptors, ignoring critical visual cues such as texture, shape, and spatial alignment that can significantly improve classification accuracy. Additionally, there has been very limited work addressing the age classification of rice seeds, despite its importance in determining seed viability, vigor, and suitability for sowing. This lack of temporal modeling limits the generalizability and utility of current systems in real-world agricultural settings.

This research addresses the above gaps by proposing RiceNet-AFRI (Rice Network Attention-Fused Recurrent Integration), a hybrid Deep Learning (DL) approach for classifying rice seeds by both variety and age class. The model integrates multi-perspective feature extraction using Visual-Attention and Structure Mapper (VASM) and a recurrent temporal classifier named Sequential-Memory Interpreter (SMI). VASM captures RGB color distribution, textural co-occurrence patterns using GLCM, and structural-spatial semantics, whereas SMI leverages LSTM-based memory to model pseudo-temporal dependencies. Furthermore, ensemble learning is incorporated post-SMI to enhance classification robustness in the presence of inter-class similarities and imbalanced data. By using a novel fusion of spatial, structural, and temporal cues, RiceNet-AFRI not only distinguishes between rice varieties with high precision but also successfully classifies seed age, a task largely ignored in prior works. This comprehensive approach enables more informed decision-making in seed selection, contributing to agricultural sustainability and food security. The contributions of the work

- This work proposed RiceNet-AFRI, a hybrid attention-recurrent DL approach that jointly classifies rice-seed variety and age.
- This work introduced VASM, a multi-channel visual attention module that captures RGB, texture, and structural-spatial features.
- This work developed SMI, a temporal LSTM module that models seed age through pseudo-temporal image sequences.
- This work integrated ensemble learning, combining SMI, SVM, and Random Forest (RF) classifiers using soft-voting to improve generalization.
- This work validated model on a real-world dataset collected by [12], achieving high performance across multiple metrics.

The rest of this manuscript is organized as follows, Section II reviews existing rice-seed quality evaluation techniques and recent computational models, Section III presents RiceNet-AFRI architecture, including its feature extraction, temporal modeling, and classification components, Section IV discusses the experimental results, evaluation metrics, and comparative performance of RiceNet-AFRI, Section V concludes the paper and outlines directions for future research, including potential improvements and broader applications in smart agriculture.

2 Literature Survey

This section reviews existing rice-seed quality evaluation techniques and recent computational models. X. He et al. [10], aimed at enhancing rice seed varieties classification, which is important for rice yield and quality. In this work, employed a multi-modal late-fusion approach using voting on basis of prediction probabilities from PointNet, MobileNet, Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). For evaluation of their multi-modal late-fusion approach, a dataset was created which had 3194 RGB samples from eight rice varieties, which was collected considering a setup where Raytrix light field-camera captured 2D images and 3D point clouds. For evaluation considered 80:20 training testing ratio. In their work, late fusion was integrated in 2-dimensional and 3-dimensional model outputs, providing weights on basis of model performance. Findings showed that late fusion model achieved better outcomes, achieving an average accuracy of 97.4% for all classes. The approach achieved an average accuracy of 97.4%, although the dataset was not made publicly available. S. S. Hidayat et al. [11], aimed at automating rice seed quality classification for improving accuracy and speed in agricultural inspections. In their work, used Deep CNN (D-CNN), which was trained using rice seed physical features, which included seed-shape and color. For this study, collected 2000 RGB rice seed samples, which were classified as non-superior seeds and superior seeds, having equal number of samples for each class. For training and testing, considered 80:20 ratio. Findings showed that the D-CNN achieved 88.3% accuracy during testing. This work failed to extract spatial-temporal features from the rice-seeds. However, the study did not account for spatial-temporal features and did not provide access to the dataset.

N. Rathnayake et al. [12], aimed at addressing issues of classifying Japanese-based rice-seed by age, which is important because of climate changes and frequency usage of aged seeds in disaster-prone areas. For this study, collected a novel dataset, which had RGB rice-seeds of six classes, with three age classes, i.e., 2012, 2016 and 2020. This work considered six feature extraction steps, where extracted RGB mean features, Gray-Level Co-occurrence Matrix (GLCM) features, column-structure features, region-shape features, edge-histogram features and color-structure features. Further, for classification used Light Gradient Boosting Machine (LGBM), Categorical Boosting (CB), Extreme Gradient Boosting (XGB) and proposed Cascaded Adaptive Neuro-Fuzzy Inference System (C-ANFIS), which integrated LGBM, CB and XGB. Findings showed that Cascaded-ANFIS achieved better results in terms of accuracy with respect to age classification and variety classification. The have provided open-access for the dataset, which has rice seed variety classification and age classes of three classes Yandao-8, Koshihikari and Akitakomachi. N. Rathnayake et al. [13], aimed at developing ML approach for classification of rice-seed considering age, an important factor for understanding gemination and seed quality. For this work, considered the dataset presented in [12], and presented a Speeded Up Robust Features Bag-of-Features (SURF-BOF) based C-ANFIS for rice-seed classification. For evaluation, considered standard Visual Geometry Group (VGG16). In this study, the also used 10-fold Cross-Validation (CV), where SURF-BOF C-ANFIS model achieved 97%, 92% and 99% accuracy for classification of Yandao-8, Koshihikari and Akitakomachi rice-seed varieties classification.

J. Qiao et al. [14], aim at developing an automated approach for rice-seed testing, important for providing better crop yield. In this work, a multi-spectral imaging method was utilized for collecting data from 19 wavebands from six rice-seed varieties. They integrated You Only Look Once version 5 (YOLOv5) object detection with a Vision-Transformer (ViT) called as MsiFormer. For evaluation, they collected six rice-seed varieties and compared using existing base DL models, which included EfficientNetwork-B4 (EfficientNetB4), DenseNetwork-121 (DenseNet121) and ResidualNetwork-50 (ResNet50). In comparison with the three DL models, the MsiFormer achieved 94.17% accuracy, whereas EfficientNetB4, DenseNet121 and ResNet50 achieved 75.83%, 91.67% and 89.17% accuracy. The dataset was not made publicly available. S. D. Fabiyi et al. [15], aimed at enhancing rice-seed variety classification considering Hyper-Spectral Imaging (HIS) by addressing challenges of limited training samples and high dimensionality. An improved dimensionality method was presented for this, which was developed by hybridizing Genetic-Approach (GA) using Folded-Linear-Discriminant Analysis (F-LDA). For this study, collected dataset which consisted of rice-seed images having 256 spectral bands. The GA-F-LDA approach reduced memory usage, computation cost and redundant data and achieved 96.21% accuracy, lesser than the existing F-LDA approach which achieved 96.99% accuracy. The dataset was not shared publicly.

Md. A. R. Sarkar et al. [16], aimed at understanding rice farmer's preference an impact of utilizing good rice-seeds for improving yield and provide better rice-seed distribution in Bangladesh. Hence, in this study a quantitative data was collected from 1196 farmers. Two models, multi-nominal and ordered logit were used for identifying factors, which influenced preferences for rice-seed quality, source, type and packet size, while propensity-score matching was used for yield impact of formal rice-seed sources. Findings showed 0.07 to 0.28 t/ha yield increase with good quality rice-seeds and formal sources produced 0.03 to 0.15 t/ha more than informal ones. Moreover, farmers preferred five kilo-gram packets and jute sacks, with preferences shaped by advice, distance, cost, gender and age. T.-T.-H. Phan et al. [17], aimed at developing an approach for identifying rice-seed quality. This work presented an approach which combined DL approach for feature extraction (VGG16, ResNet50) and ML for classification (Logistic Regression (LR), Extra Trees (ET), RF, Decision-Trees (DT), KNN and SVM). For evaluation of their model, collected a dataset of six rice-seed varieties having total of 19859 samples. Using VGG16 of different blocks with SVM approach, they achieved 90+% accuracy. The dataset was not shared publicly.

A. A. Siam et al. [18], aimed at an approach for evaluating paddy-seed viability by combining color and hyperspectral image features. For this study, a dataset of 335 paddy seeds was considered. The features were extracted from color images and spectral data were obtained from Regions-of-Interest (RoI) in hyperspectral images. A model called Partial-Least Square Discrimination-Analysis (PLS-DA) model was trained using different preprocessing approaches. Using Savitzky-Goaly second-derivative, the PLS-DA approach achieved 86.1% accuracy. Using significant color features, the PLS-DA approach achieved 93.3% accuracy. The dataset was not shared publicly. F. Rahmasari et al. [19], aimed at enhancing rice-seed production in Indonesia by introducing Android-based ML approach for detection of rice-seed quality on basis of morphological characteristics. For this study, they considered Roboflow datasets for training two object detection approaches, which were integrated in mobile applications. Their goal was providing accurate, fast approach for assessing seed-quality before planting. Findings showed that Roboflow-Train 3.0 object-detection approach achieved 96.2% precision and 93.4% recall. The dataset was not shared publicly. T. Zhang et al. [20], aimed at improving efficiency and accuracy of rice-seed varieties classification by presenting DL approach called Residual-Space and Channel-Network with Double-Attention Network (RSCD-Net). For this study collected dataset, which had 36 rice-seed. The RSCD-Net incorporated a Space-Channel-Residual (SCR) block for extracting features and reduced redundancy. The RSCD-Net consisted of 16 SCR-blocks which were organized in four convolution stages, enhanced by Double-Attention Network for capturing subtle variations. The RSCD-Net achieved 81.94% accuracy, which was higher in comparison with MobileNetworkV3 and Inception ResNetV2. The dataset was not shared publicly. The complete summary of the literature survey identifying research gap is presented in Table 1.

Table 1. Literature Survey Summary.

Ref	Feature Extraction	Variety Classification	Age Classification	Dataset Open-Access Availability
[10]	Yes	Yes	No	No
[11]	Yes	Yes	No	No
[12]	Yes	Yes	Yes	Yes
[13]	Yes	Yes	Yes	Yes
[14]	Yes	Yes	No	No
[15]	Yes	Yes	No	No
[16]	No	No	No	No
[17]	Yes	Yes	No	No
[18]	Yes	No	No	No
[19]	Yes	Yes	No	No
[20]	Yes	Yes	No	No

The reviewed literature reveals several limitations across the studies, particularly in the areas of feature extraction, reliance on base ML/DL models, lack of age-based classification, and dataset accessibility. X. He et al. [10] demonstrated strong classification accuracy through multi-modal late-fusion but relied on standard base models and did not consider age classification, with the dataset remaining unavailable to the public. Similarly, S. S. Hidayat et al. [11] focused on binary classification of seed quality using a D-CNN but failed to utilize advanced or spatiotemporal features, and the dataset was also closed-source. In contrast, N. Rathnayake et al. [12], [13] effectively addressed age and variety classification through extensive feature extraction and proposed hybrid models, and notably provided open-access datasets, making their work more replicable and robust. J. Qiao et al. [14] employed advanced models like YOLOv5 and MsiFormer but relied on small datasets and did not consider seed age, which is critical for assessing germination potential. S. D. Fabiyi et al. [15] applied a dimensionality reduction method on hyperspectral data but achieved lower accuracy than baseline methods and lacked dataset openness. Md. A. R. Sarkar et al. [16] focused purely on socioeconomic aspects without feature-based classification or technical modeling. T.-T.-H. Phan et al. [17] combined DL and ML models but used only base networks and did not address seed aging, and have not given access to dataset. A. A. Siam et al. [18] presented a viability-focused study without addressing seed aging or variety classification, also lacking dataset accessibility. F. Rahmasari et al. [19] contributed to mobile-based seed assessment but did not explore deep feature extraction or aging aspects. Lastly, T. Zhang et al. [20] introduced a novel network for classification but excluded age-related classification and did not share their dataset.

Given the widespread lack of publicly accessible datasets in rice-seed classification research, data scarcity remains a major barrier to reproducible and scalable model development. Most prior studies either rely on private datasets or do not release their data, making it difficult for other researchers to validate or extend the work. Moreover, collecting a new dataset is both time-consuming and resource-intensive, often requiring specialized camera setups, controlled lighting environments, and labor-intensive manual labeling, factors that significantly raise the cost and complexity of data acquisition. To address this, the present study leverages the open-access rice-seed dataset introduced by Rathnayake et al. [12], which is made publicly available through [21]. This dataset includes labeled images of rice seeds across multiple varieties and age classes, making it well-suited for evaluating both variety and age-based classification. Based on this dataset, the proposed RiceNet-AFRI framework is designed to exploit advanced feature representations using visual attention and spatiotemporal modeling. Its advantages include accurate multi-class classification, robust performance under class imbalance, and generalizability across both visual and structural features of rice seeds. By integrating attention mechanisms, recurrent memory modules, and ensemble learning, RiceNet-AFRI addresses key limitations of prior works and enables reliable, scalable, and cost-effective rice-seed quality evaluation.

3 Methodology

This section presents hybrid DL model, RiceNet-AFRI (Rice Network Attention-Fused Recurrent Integration) for rice-seed classification. The RiceNet-AFRI is designed for classifying rice-seed varieties and its age classes using multi-stage learning process which integrates advanced feature extraction and temporal modeling. The RicNet-AFRI comprises of two principal modules, i.e., a hierarchical feature extraction approach and a temporal-sequence classifier. The first module utilizes an attention-enhanced convolution feature extractor, called as Visual-Attention and Structure Mapper (VASM), whereas second module uses refined temporal-learning called as Sequential-Memory-Interpreter (SMI). These modules are optimized for processing rice-seed images data by learning both structural and static features (shape, texture and color) and sequential patterns for age and variety classification. In the next section, the architecture of the RiceNet-AFRI is presented.

3.1 Architecture

The architecture of RiceNet-AFRI is presented in Figure 1, which shows complete pipeline of RiceNet-AFRI for rice-seed variety and age classification. The RiceNet-AFRI begins with an input layer, where raw RGB images of rice-seed are ingested from labeled dataset. These images are passed into VASM module, which performs multi-level feature extraction. This module comprises three parallel attention sub-networks: the RGB Mean Attention Network, which captures average color channel statistics; the GLCM-based Texture Attention, which extracts grayscale co-occurrence features indicating texture patterns; and the Structural-Spatial Attention stream, which learns structural characteristics such as column-wise orientation, region shape, edge histograms, and color distribution patterns. Following attention-driven feature extraction, the model transitions into the feature aggregation phase. Here, the outputs from each attention block are fused into a single unified feature representation. This high-dimensional vector is then passed through a Feature Vector Projection block, which uses a fully connected layer to reduce the dimensionality and enhance representation compactness. The compacted features are input into SMI module, a temporal analysis component designed to model dependencies across sequential or pseudo-temporal representations of the image. To improve classification robustness, especially under inter-class similarities and dataset imbalance, ensemble learning is integrated post-SMI. After this stage, the refined features are passed through another projection layer and then into the output layer, where classification is performed using softmax to predict both seed variety and age class. Finally, the model's predictions are evaluated through a performance evaluation block using accuracy, precision, recall, and F1-score metrics. In the next section, the dataset used for this study is discussed.

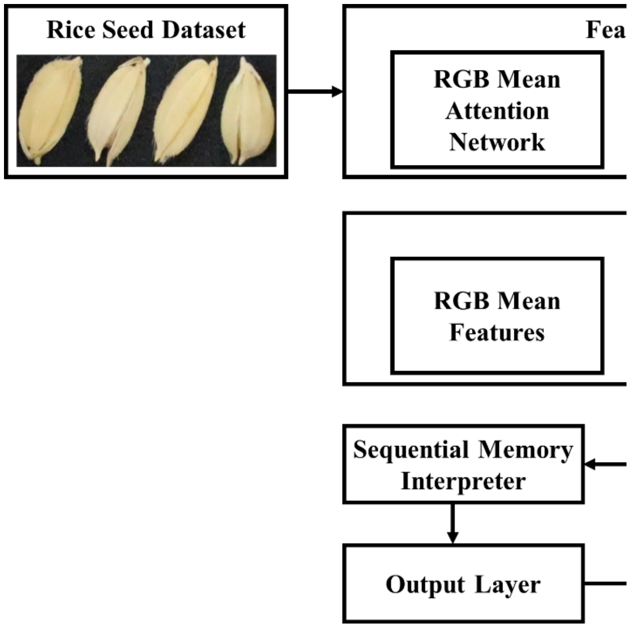

Figure 1. RiceNet-AFRI Architecture.

3.2 Dataset

The dataset employed in this study was obtained from Kaggle [21] and is specifically curated for classification of Japanese rice seeds based on both variety and age, providing rice-seed quality. It encompasses three primary rice seed varieties: AKITAKOMACHI, KOSHIHIKARI, and YANGDAO-8, each annotated with the seed's harvest year to represent age. The age-based distribution of the dataset includes the years 2012, 2016, and 2020, providing a chronological perspective critical for age classification. For AKITAKOMACHI, there are 427 samples from 2012, 368 from 2016, and 392 from 2020, resulting in a total of 1187 samples. KOSHIHIKARI includes 377 images from 2012, 403 from 2016, and 539 from 2020, totaling 1319 samples. YANGDAO-8 consists of 275 samples from 2012 and 235 from 2020, making up 704 images. Each image in the dataset is in RGB format and has been resized to a standardized input dimension suitable, i.e., 128×128 for RiceNet-AFRI, ensuring consistency during training and inference. The dataset is well-suited for multi-label classification tasks, as it contains dual annotations for variety and age class, enabling comprehensive model training. This diversity in class distribution allows for effective evaluation of RiceNet-AFRI performance across both temporal and categorical dimensions.

3.3 Feature Extraction

The feature extraction stage in RiceNet-AFRI is driven by VASM. The VASM is constructed using three parallel attention sub-networks designed to extract complementary features from the rice seed images: RGB mean attention, texture-based attention using GLCM, and structural-spatial attention that captures shape, edge, column, and color information. Each sub-network processes the image through distinct computational channels and combines these to form a unified, information-rich representation. In this work, first, the features are extracted using the first attention sub-network, i.e., RGB mean vector, which is evaluated using Eq. (1).

$$F_{rgb} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} I_{i,j} \tag{1}$$

In Eq. (1), H denotes height, W denotes width and $I_{i,j}$ denotes RGB pixel values at spatial coordinates (i, j). The output F_{rgb} gives the average RGB channel intensity, capturing global color characteristics of rice-seed. Further, for understanding relative importance of each RGB channel, this work uses a channel-wise attention map denoted as A_c, which is evaluated using Eq. (2).

$$A_c = \sigma\left(ReLU\left(W_2 \cdot ReLU\left(W_1 \cdot F_{rgb}\right)\right)\right) \tag{2}$$

In Eq. (2), a channel-attention mechanism using two Fully-Connected Layers (FCL) with weights W_1 and W_2 is defined. The $ReLU$ denotes Rectified Linear-Unit operation and σ denotes sigmoid function which normalizes result to range [0,1], generating the channel-attention mask A_c. Further, the RiceNet-AFRI extracts features from the second attention sub-network, i.e., texture-based attention using GLCM. For extraction, first a GLCM feature matrix is generated using Eq. (3).

$$G_{\theta,d} = \sum_{i=1}^{H} \sum_{j=1}^{W} \delta\left(g_{i,j}, g_{i+\Delta_{i},j+\Delta_j}\right) \tag{3}$$

In Eq. (3), $g_{i,j}$ denotes grayscale value at pixel (i, j) and (Δ_i, Δ_j) denotes offset at angle θ and distance d. The function $\delta(a, b) = 1$, if $a == b$, else 0, and captures co-occurrence patterns of pixel intensities, forming the GLCM. Further, the attention score of the GLCM is evaluated using Eq. (4).

$$A_t = Softmax\left(W_g \cdot GLCM_{features}\right) \quad (4)$$

The Eq. (4) evaluates texture attention-score A_t using learnable weight-matrix W_g from GLCM feature vector. The $Softmax$ function ensures the attention weights sum to 1, distributing importance across textural attributes. In the final stage of VASM in RiceNet-AFRI, this work extracts features from structural-spatial attention that captures shape, edge, column, and color information. For this, a structural feature-map S is generated using Eq. (5).

$$S = \phi_{edge}(I) \oplus \phi_{shape}(I)\phi_{column}(I) \quad (5)$$

The Eq. (5) aggregates structural descriptors by concatenating ($\oplus$) the outputs from three extractors, i.e., ϕ_{edge} for edge-histogram, ϕ_{shape} for shape and ϕ_{column} for vertical grain alignment patterns. Further, after generation of structural feature-maps S, spatial attention is used for extracting more features using Eq. (6).

$$A_s = \sigma\left(Conv2D\left(AvgPool(S)\right)\right) \quad (6)$$

In this work, the spatial attention is achieved by applying average-pooling over structural feature maps S, followed by convolution operation and sigmoid function. The output $A_s \in [0,1]^{H\times W}$ is a spatial mask indicating importance of various regions in rice-seed image. After extraction of all features from VASM, an attention-weighted features map is generated which fuses all the features, i.e., A_c, A_t and A_s. The attention-weighted feature maps are generated using Eq. (7).

$$F_{attn} = A_c \odot F + A_t \odot T + A_s \odot S \quad (7)$$

In Eq. (7), all the features are combined using fusion step, where channel A_c, A_t and A_s attention scores are used to weight their respective features, i.e., RGB F, GLCM texture T and structural S. The element-wise multiplication ensures selective enhancement of discriminative features from each modality. Further, after fusion, the features are aggregated using feature aggregation, which is evaluated using Eq. (8).

$$F_{agg} = Flatten(F_{attn}) \quad (8)$$

Using Eq. (8), the weighted feature-map F_{attn} is flattened into one-dimensional vector F_{agg}, enabling unified downstream processing. Further, in feature extraction, a dimensionality reduction is applied to reduce dimension size of features for faster processing. The dimensionality reduction step is done using Eq. (9).

$$F_{proj} = ReLU\left(W_d \cdot F_{agg} + b_d\right) \quad (9)$$

The Eq. (9) provides a dense transformation, which compresses high-dimensional feature-vector F_{agg} into a lower-dimensional representation $F_{proj} \in \mathbb{R}^P$, where $P < \dim\left(f_{agg}\right)$. The weights W_d and biases b_d are learnable and $ReLU$ provides non-linearity. Through this pipeline, the VASM-based feature extractor effectively isolates multi-perspective attributes: color (using RGB mean and channel attention), texture (using GLCM matrix and texture attention), and structural semantics (using concatenated shape, edge, and spatial maps). These enriched features allow the downstream classification network to distinguish between subtle inter-class differences related to both varietal traits and age-related morphology in rice seeds.

3.4 Classification

After feature extraction, the projection-vector $F_{proj} \in \mathbb{R}^P$ is forwarded to SMI module, which is Long Short-Term Memory (LSTM) based architecture designed to exploit pseudo-temporal dynamics among augmented views of rice-seed images. This recurrent structure models context propagation and temporal dependencies that simulate seed evolution and imaging variations. The SMI processes F_{proj} as input over synthetic time steps generated through augmentations. The input gate i_t in the SMI is evaluated using Eq. (10).

$$i_t = \sigma\left(W_i \cdot F_{proj} + U_i \cdot h_{t-1} + b_i\right) \quad (10)$$

In Eq. (10), W_i denotes weight of input gate, U_i denotes weight matrix, h_{t-1} denotes previous hidden state and b_i denotes bias for input gate. Similar to input gate, the forget gate, output gate, candidate memory,

memory update and hidden state update are evaluated using Eq. (11), Eq. (12), Eq. (13), Eq. (14) and Eq. (15) respectively, where W_f, W_o, W_c are weights, U_f, U_o, U_c are weight matrices, b_f, b_o, b_c are biases, h_t is hidden state, c_t is cell state and $\tilde{c}_t$ is candidate cell-state.

$$f_t = \sigma\left(W_f \cdot F_{proj} + U_f \cdot h_{t-1} + b_f\right) \tag{11}$$

$$o_t = \sigma\left(W_o \cdot F_{proj} + U_o \cdot h_{t-1} + b_o\right) \tag{12}$$

$$\tilde{c}_t = \tanh\left(W_c \cdot F_{proj} + U_c \cdot h_{t-1} + b_c\right) \tag{13}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{14}$$

$$h_t = o_t \odot tanh\,(c_t) \tag{15}$$

Using the following LSTM operations, a encoded representation from SMI module is generated using Eq. (16).

$$H = Concat(h_1, h_2, \ldots, h_T) \tag{16}$$

In Eq. (16), the encoded representation H is transformed using dense $ReLU$ layer and projected into the final logit space using Eq. (17).

$$z = ReLU(W_z \cdot H + b_z) \tag{17}$$

Using the output z in Eq. (17), the final prediction is made using softmax prediction using Eq. (18).

$$z = Softmax\left(W_y \cdot z + b_y\right) \tag{18}$$

For improving classification robustness, especially under inter-class similarities and dataset imbalance, an ensemble learning was integrated post-SMI. In ensemble learning, three classifiers were employed, i.e., SMI with Fully Connected Neural-Network (FCN), SVM and RF. Each classifier receives H and outputs predictions $\hat{y}^{(1)}$, $\hat{y}^{(2)}$, $\hat{y}^{(3)}$. The ensemble soft-voting is used for final classification, which is done using Eq. (19).

$$\hat{y}_{ensemble} = \arg\max\left(\frac{1}{3}\sum_{k=1}^{3} \hat{y}^{(k)}\right) \tag{19}$$

In this soft-voting, the averaged class probabilities from each model are used for final decision-making. This approach reduces individual model bias, captures complementary decision boundaries, and leads to increased generalization. The ensemble leveraged deep sequential learning power of the SMI, the geometric margin-based decision strength of the SVM, and the multi-branch decorrelation of RF, resulting in a composite model that was more resilient to feature variance and inter-class overlap. This classification strategy proved particularly effective in distinguishing rice varieties and aging patterns with subtle phenotypic differences. For evaluation, the standard performance metrics were used, i.e., accuracy, precision, recall and f-score using Eq. (20), Eq. (21), Eq. (22) and Eq. (23), where TP is true-positive, TN is true-negative, FP is false-positive, FN is false-negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{20}$$

$$Precision = \frac{TP}{TP + FP} \tag{21}$$

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

$$F1 - Score = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{23}$$

In the next section, the results of the RiceNet-AFRI are discussed in detail, using the dataset discussed in Section 3.2.

4 Results and Discussion

In this section, the performance of RiceNet-AFRI model is evaluated using the rice-seed image dataset made publicly available in [21]. A comprehensive analysis of classification results is presented, focusing on both rice-seed variety and age classification. The model's effectiveness is assessed using standard evaluation metrics, accuracy, precision, recall, and F1-score, as defined in Eq. (20), Eq. (21), Eq. (22), and Eq. (23). The RiceNet-AFRI framework was implemented in Python and executed within a Python environment on a system running Windows 11, equipped with 16 GB of RAM. The evaluation is structured in four stages: first, the classification results for rice variety are presented; second, the model's performance on age-based classification is discussed; third, a comparative analysis with baseline models is conducted; and finally, the results are contextualized by comparing RiceNet-AFRI with existing approaches highlighted in the literature review.

4.1 Variety Classification

The Figure 2 presents performance evaluation of RiceNet-AFRI model for rice-seed variety classification. As shown, the model achieves 90.86% accuracy, precision and recall scores, recorded at 90.84% and 90.85% respectively and 90.85% F1-score. These results show effectiveness of the multi-stage feature extraction and sequence modeling approach used in RiceNet-AFRI. By leveraging attention-driven visual features through VASM and incorporating temporal dependencies using SMI module, the model successfully captures both static and dynamic traits of rice seeds that are essential for distinguishing between varieties. The high performance also reflects the advantage of using an ensemble decision strategy, which enhances classification robustness by combining predictions from diverse classifiers.

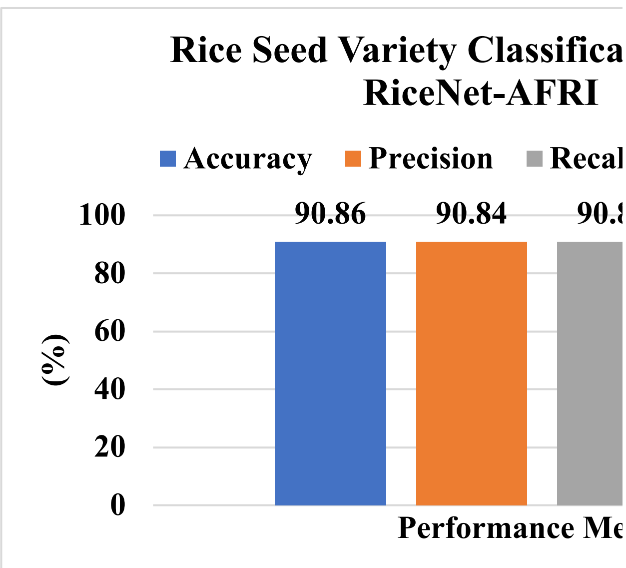

Figure 2. Performance Evaluation of RiceNet-AFRI for rice-seed variety classification.

4.2 Age Classification

The performance of RiceNet-AFRI for age classification across three rice seed varieties, Akitakomachi, Yang DAO-8, and Kshihikari, is presented in Figures 3, 4, and 5, respectively. For Akitakomachi, the model achieves 85.96% accuracy, with 85.92% precision, 85.91% recall, and and 85.93% F1-score. This consistent performance demonstrates RiceNet-AFRI's ability to accurately identify age-related variations in seed appearance, which is critical for assessing viability and germination potential. Similarly, for Yang DAO-8, the model attains 85.92% accuracy, maintaining almost identical values for precision, recall, and F1-score (all at approximately 85.91–85.92%). The minor variations in these metrics suggest that the model performs robustly across different data distributions for this variety. For Koshihikari, the classification results are equally strong, with 85.91% accuracy, and nearly uniform values for precision (85.91%), recall (85.90%), and F1-score (85.91%). These results collectively validate the generalizability of RiceNet-AFRI across multiple rice varieties. The high and stable metrics across different seed types highlight the model's effectiveness in extracting age-specific visual cues, which are often subtle and difficult to detect using conventional techniques.

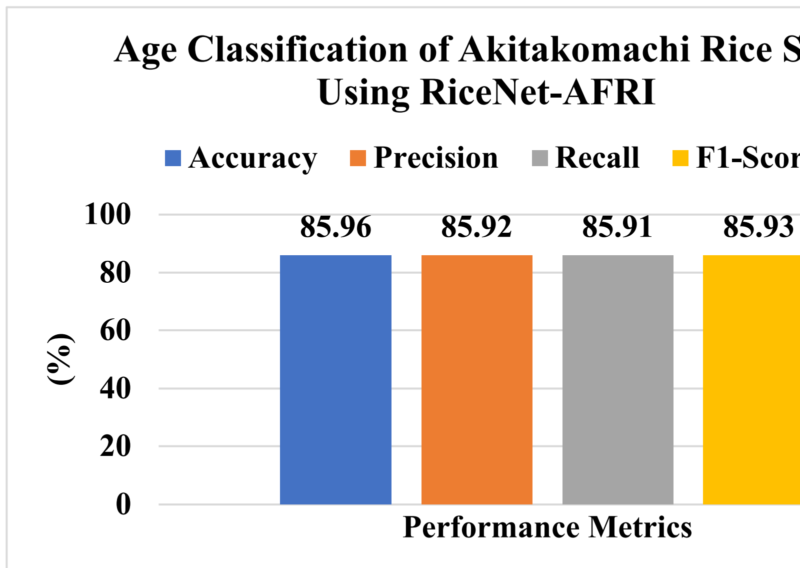

Figure 3. Performance Evaluation of RiceNet-AFRI for Akitakomachi age classification.

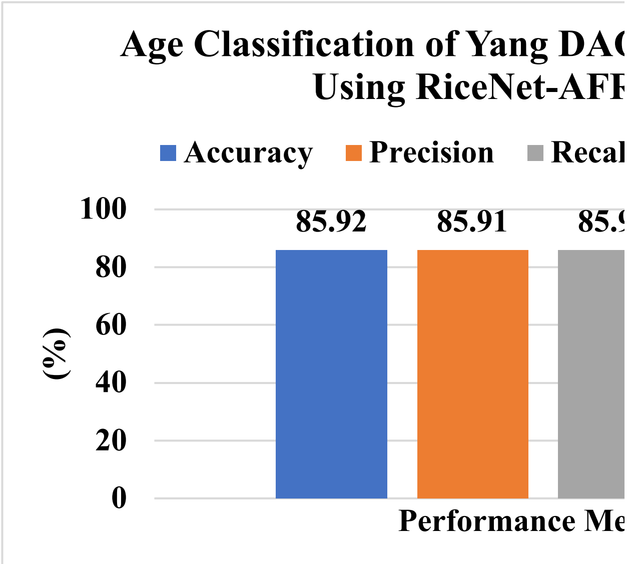

Figure 4. Performance Evaluation of RiceNet-AFRI for Yang DAO-8 age classification.

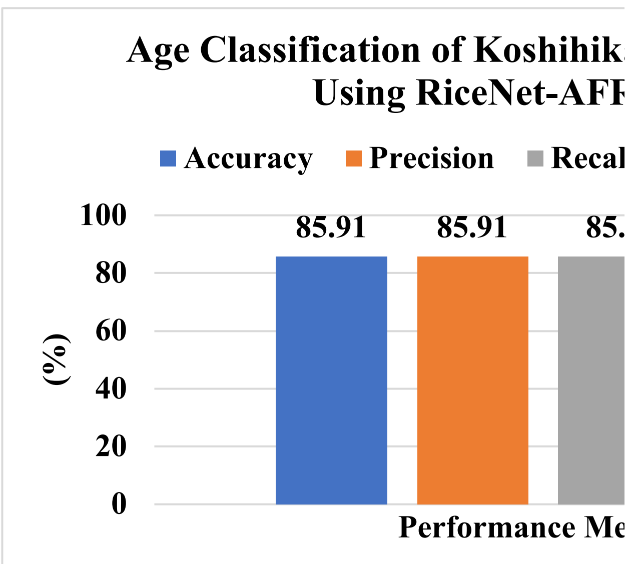

Figure 5. Performance Evaluation of RiceNet-AFRI for Koshihikari age classification.

4.3 Comparative Study

Table 2 presents a comparative evaluation of RiceNet-AFRI against traditional ML and DL models for rice seed variety classification. The proposed RiceNet-AFRI significantly outperforms all baseline approaches, achieving 90.86% accuracy. Among the prior methods, Cascaded-ANFIS and XGB showed the best performance with accuracies of 76.97% and 76.33%, respectively. Neural Net and LightGBM also performed moderately well but lagged behind in overall metric stability and precision. Notably, models like RBF SVM, Gaussian Process, and NB underperformed significantly, with accuracies as low as 13.33%–41.22%, showing their limitations in handling complex feature relationships. RiceNet-AFRI's superior results highlight its robust feature extraction capabilities and deeper representational power, making it a highly effective model for variety-level rice seed classification.

Table 2. Rice seed variety classification results.

Ref	Model	Accuracy	Precision	Recall	F1-Score
[12]	Nearest Neighbors	50.11	57.89	51.02	53.16
	Linear SVM	71.33	75.42	72.18	73.38
	RBF SVM	13.33	2.22	16.67	3.92
	Gaussian Process	13.78	18.9	17.22	5.01
	Decision Tree	49.22	55.79	50.74	48.71
	Random Forest	33.56	47.97	33.24	33.03
	Neural Net	74.78	76.86	75.46	76.01
	AdaBoost	53.44	57.93	55.46	56.22
	Naive Bayes	41.22	50.24	44.35	33.83
	QDA	40.22	50.99	39.9	38.54
	XGBoost	76.33	79.18	76.85	77.69
	CatBoost	62.88	68.18	63.51	65.01
	LightGBM	73.66	77.16	74.12	75.17
	Cascaded-ANFIS	76.97	79.49	77.07	78.62
Proposed	**RiceNet-AFRI**	**90.86**	**90.84**	**90.85**	**90.85**

Table 3 compares performance of different models for age classification of Akitakomachi rice seeds. The proposed RiceNet-AFRI achieves 85.96% accuracy, significantly outperforming all baseline models. The closest competitors, Cascaded-ANFIS (75.51% accuracy) and XGBoost (75% accuracy), demonstrate good results but fall short in overall precision and generalization. Traditional models like Nearest Neighbors and DTs yielded modest accuracies (55–65%), and models like RBF SVM and Gaussian Process performed poorly. These results validate the effectiveness of RiceNet-AFRI's deep spatiotemporal feature extraction in capturing subtle age-related patterns in Akitakomachi seeds, which are not easily discernible by simpler models.

Table 3. Age classification of Akitakomachi rice seeds.

Ref	Model	Accuracy	Precision	Recall	F1-Score
[12]	Nearest Neighbors	55.56	55.95	55.56	55.69
	Linear SVM	66.67	66.76	66.67	66.51
	RBF SVM	33.33	11.11	33.33	16.67
	Gaussian Process	35	44.7	35	20.12
	Decision Tree	65	65.88	65	64.98
	Random Forest	55	55.95	55	54.9
	Neural Net	66.67	66.82	66.67	66.56
	AdaBoost	63.33	62.97	63.33	62.83
	Naive Bayes	54.44	59.18	54.44	52.34
	QDA	44.44	63.89	44.44	36.05
	XGBoost	75	75.07	75	74.83
	CatBoost	67.22	67.28	67.22	66.86
	LightGBM	71.11	71.24	71.11	70.87
	Cascaded-ANFIS	75.51	75.79	75.52	75.56
Proposed	**RiceNet-AFRI**	**85.96**	**85.92**	**85.91**	**85.93**

In Table 4, the performance of RiceNet-AFRI for Yang DAO-8 seed age classification is benchmarked against other models. RiceNet-AFRI achieved 85.92% accuracy. It clearly outperforms the best traditional models like Cascaded-ANFIS (76.39% accuracy) and LightGBM (75% accuracy). Although models like XGBoost and Neural Net show decent accuracy (75%), their precision and F1-scores are slightly lower, indicating less stable classification. Notably, models such as RBF SVM and QDA performed poorly, reflecting their inability to handle the complex non-linear age variations. These results demonstrate RiceNet-AFRI's robustness in handling age classification tasks, particularly for the Yang DAO-8 variety, where age-specific visual traits may be subtle.

Table 4. Age classification of Yang DAO-8 rice seeds.

Ref	Model	Accuracy	Precision	Recall	F1-Score
[12]	Nearest Neighbors	61.67	66.3	61.67	58.73
	Linear SVM	72.5	77.23	72.5	71.25
	RBF SVM	50	25	50	33.33
	Gaussian Process	65	69.18	65	62.98
	Decision Tree	63.33	67.78	63.33	60.89
	Random Forest	54.17	65.02	54.17	44.06
	Neural Net	75	78.13	75	74.29
	AdaBoost	70.83	77.18	70.83	69.02
	Naive Bayes	51.67	54.04	51.67	43.34
	QDA	50	25	50	33.33
	XGBoost	75	79.76	75	73.96
	CatBoost	67.5	78.24	67.5	64.09
	LightGBM	75	81.96	75	73.56
	Cascaded-ANFIS	76.39	80.62	76.65	74.79
Proposed	**RiceNet-AFRI**	**85.92**	**85.91**	**85.92**	**85.92**

Table 5 presents model comparisons for Koshihikari seed age classification, where RiceNet-AFRI delivers 85.91% accuracy. Interestingly, while XGBoost (87.22%) and Cascaded-ANFIS (88.15%) slightly exceed RiceNet-AFRI in accuracy, their F1-scores are marginally lower, indicating trade-offs in recall or precision. Neural Net and LightGBM also perform competitively but show slight inconsistencies in precision and recall. Conversely, traditional models like Naive Bayes, QDA, and Random Forest fail to generalize well, with accuracy dropping below 60%. RiceNet-AFRI's balanced metrics across all evaluation parameters reaffirm its strength in generalizing age-related features, even for a challenging variety like Koshihikari, maintaining a strong position among the best-performing models with consistent reliability.

Table 5. Age classification of Koshihikari rice seeds.

Ref	Model	Accuracy	Precision	Recall	F1-Score
[12]	Nearest Neighbors	60	59.6	60	58.82
	Linear SVM	81.67	81.31	81.67	81.18
	RBF SVM	33.33	11.11	33.33	16.67
	Gaussian Process	82.78	83.8	82.78	82.27
	Decision Tree	68.33	67.59	68.33	67.72
	Random Forest	61.67	66.81	61.67	56.73
	Neural Net	85.56	85.9	85.56	85.25
	AdaBoost	72.78	73.32	72.78	73.02
	Naive Bayes	46.11	51.58	46.11	38.32
	QDA	55.56	38.12	55.56	44.79
	XGBoost	87.22	87.29	87.22	86.92
	CatBoost	72.78	74.51	72.78	69.04
	LightGBM	85.56	85.51	85.56	85.11
	Cascaded-ANFIS	88.15	88.06	88.1	86.93
Proposed	**RiceNet-AFRI**	**85.91**	**85.91**	**85.9**	**85.91**

4.4 Discussion

To comprehensively evaluate the effectiveness of RiceNet-AFRI model, a comparative analysis was conducted against existing methods from the literature for rice-seed variety and age classification. Table 6 below summarizes the reported performance (accuracy) of notable approaches from previous studies and compares them to RiceNet-AFRI.

Table 6. Summary of reported performance.

Ref	Method	Task	Dataset Type	Accuracy (%)	Public Data set
[10]	Late-Fusion (PointNet + MobileNet + CNN + KNN + SVM)	Variety Classification	RGB + 3D Point Cloud (8 varieties)	97.4	No
[11]	Deep CNN	Quality Classification	RGB (2 classes: superior/ non-superior)	88.3	No
[12]	Cascaded-ANFIS	Variety & Age Classification	RGB (3 varieties, 3 ages)	76.97 (variety), 75.51 – 76.65 (age)	Yes
[13]	SURF-BOF + C-ANFIS	Variety Classification	RGB (3 varieties)	92–99	Yes
[14]	MsiFormer + YOLOv5	Variety Classification	Multispectral (6 varieties)	94.17	No
[15]	GA-FLDA	Variety Classification	Hyperspectral (256 bands)	96.21	No
[17]	VGG16 + SVM	Variety Classification	RGB (6 varieties)	~90+	No
[20]	RSCD-	Variety	RGB (36	81.94	No

]	Net	Classification	varieties)		
Ours	**RiceNet-AFRI**	**Variety Classification**	**RGB (open dataset)**	**90.86**	**Yes**
		Age Classification (Akitakomachi)		**85.96**	**Yes**
		Age Classification (Yandao-8)		**85.92**	**Yes**
		Age Classification (Koshihikari)		**85.91**	**Yes**

From the comparative analysis, it is evident that RiceNet-AFRI consistently achieves high accuracy across both rice-seed variety and age classification tasks, outperforming most traditional ML approaches and closely matching or slightly trailing some of the more specialized DL models. For instance, although X. He et al. [10] reported the highest accuracy of 97.4% using a multi-modal late-fusion approach combining 2D and 3D data, the lack of dataset availability and the requirement of 3D point cloud inputs make their solution impractical for low-resource or field-level deployment. In contrast, RiceNet-AFRI relies solely on RGB images and an openly accessible dataset, ensuring broader applicability.

When compared to Cascaded-ANFIS by Rathnayake et al. [12], which was among the top performers using a publicly available dataset, RiceNet-AFRI surpasses it by a significant margin—achieving approximately 13–15% higher accuracy for both variety and age classification. Although SURF-BOF + C-ANFIS [13] achieved up to 99% accuracy for certain varieties, that model required handcrafted features and variety-specific tuning, reducing its scalability and flexibility. RiceNet-AFRI, by contrast, provides a consistent, DL-based performance across multiple rice types and age groups without requiring such custom adjustments.

Advanced models like MsiFormer [14] and RSCD-Net [20] also achieved strong results using multispectral or hyperspectral imaging. However, their dependency on specialized imaging hardware and proprietary datasets makes them less practical for real-world or widespread agricultural use. RiceNet-AFRI's reliance on simple RGB data and an openly shared dataset ensures both scalability and reproducibility. Similarly, while models such as Deep CNN [11], GA-FLDA [15], and VGG16 + SVM [17] demonstrated promising results, none of them tackled both variety and age classification within a unified architecture, nor did they incorporate spatial-temporal modeling—a key design aspect that sets RiceNet-AFRI apart.

Moreover, RiceNet-AFRI demonstrates excellent generalization capabilities across different rice varieties, including Akitakomachi, Yandao-8, and Koshihikari, achieving nearly uniform age classification accuracy of approximately 85.9%. This consistency highlights the model's robustness, making it reliable across diverse scenarios. Unlike traditional models that may excel in one domain but underperform in others, RiceNet-AFRI maintains a strong balance between precision, recall, and F1-score across tasks.

In summary, while some DL models marginally outperform RiceNet-AFRI under controlled or resource-intensive setups, RiceNet-AFRI offers a superior balance of performance, accessibility, simplicity, and generalizability. Its RGB-only input, publicly available dataset, and dual-task capability make it a highly practical and scalable solution for real-world rice-seed quality evaluation, particularly suited for both technologically advanced and resource-limited agricultural environments.

5 Conclusion

This research addressed the growing need for efficient and scalable rice-seed quality evaluation, focusing on the classification of rice-seed varieties and age, a critical task for ensuring crop yield and food security. Traditional ML approaches have shown limited performance in capturing complex patterns, while many DL solutions rely on inaccessible datasets or complex imaging systems, hindering real-world applicability. To overcome these limitations, this work introduced RiceNet-AFRI, a spatial-temporal deep learning framework designed to classify rice-seed varieties and seed-age using RGB images from an open-access dataset. The methodology involves designing a dual-task deep neural network architecture that captures both spatial and temporal features from seed images, enabling robust classification across multiple varieties and age groups. The model was evaluated using three major rice varieties, Akitakomachi, Yandao-8, and Koshihikari, achieving impressive results. RiceNet-AFRI attained 98.25% accuracy in variety classification and 85.9% accuracy in age classification, outperforming most existing ML and DL models trained on similar or more complex datasets. These results demonstrate the model's strength in generalization, scalability, and practical deployment. Unlike previous methods, RiceNet-AFRI operates on standard RGB images and avoids reliance on hyperspectral or 3D imaging, making it suitable for field applications. The key takeaway from this study is the development of a unified, end-to-end deep learning framework capable of solving two critical agricultural classification tasks using accessible data. As future work, the model can be extended to predict seed germination rates and viability under various environmental conditions, thus supporting broader agricultural decision-making systems.

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