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Research Article

Dual-Branch Shape Texture Learning With Pyramid Residual and Sobel Edge Layers for Rice Variety Classification

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Abstract: Automated rice variety classification categorizes rice types based on features, such as grain texture, shape, color, and size. Traditional handcrafted feature-based models fail at rice classification due to lighting variations, background noise, and environmental conditions, leading to overlapping visual characteristics and frequent misclassification. To address these challenges, this research proposes a novel Dual-Branch Convolutional Neural Network with Pyramid Residual Units and a Sobel Edge Layer (DB-PRU-SEL) for rice variety classification. The DB-PRU-SEL consists of two branches: The first extracts robust shape features using hierarchical PRU to capture multi-scale structural details, while the second focuses on texture by integrating Sobel edge detection with convolutional layers. The outputs from both branches are concatenated by an attention-guided feature fusion mechanism that selectively enhances the discriminative features before passing them through fully connected layers for final classification. DB-PRU-SEL achieves superior performance on a rice image dataset, attaining an accuracy of 99.87% and an Area Under the Curve (AUC) of 99.99%, respectively. Comparative and ablation studies demonstrate that DB-PRU-SEL outperforms conventional classifiers. Additionally, complexity analysis indicates reduced training time and memory usage, making it an efficient solution for rice variety classification.

Keywords: Attention-Guided Feature Fusion, Discriminative Feature, Multi-Scale Structural Feature, Pyramid Residual Units, Rice Variety Classification, Sobel Edge Layer

Introduction

According to the Food and Agriculture Organization (FAO), agriculture plays the most important role in the economy of developing nations, with approximately 39.4% of the Gross Domestic Product (GDP) attributable to agriculture and almost 67% of the world population involved in agricultural activities (Din et al., 2024). Rice is the third most widely cultivated crop after sugarcane and maize. Different species of rice are imported and traded on the global market, making it an essential economic pillar in many countries (Kiratiratanapruk et al., 2020). In addition to being nutritionally valuable, rice is a major agricultural product that greatly enhances farmers' livelihoods (Razavi et al., 2024a). Buyers' rejection of poor-quality produce poses financial risks, highlighting the importance of precise and effective methods for detecting rice quality (Weng et al., 2020; Islam et al., 2025a). Rice is a staple food that has a major influence on global food security and livelihoods. The growing demand for high-quality rice requires the implementation of modern agricultural technologies (Chen et al., 2024; He et al., 2023). Asia is the leading producer of rice, and China has been the top producer of rice annually, with 28.90% of world output produced in 2018 (Meng et al., 2022). The quality of rice in China depends on the region because of variations in temperature, soil content, and moisture (Wijayanto et al., 2023). High-quality rice usually contains vital constituents, such as starch, amino acids, proteins, and trace microelements, making it sought after by end users and agricultural traders (Chai et al., 2024).

Rice classification is considered a fine-grained computer vision problem that attempts to automatically classify and detect various rice varieties, judging by their appearance as grains (Patel and Sharaff, 2023). An image of a rice grain is used as the input, and the system is used to produce a matching category label (Ritharson et al., 2024). The chief difficulties are subtle visual similarities, dataset imbalance, and noise interference in a real environment (Iqbal et al., 2023). Farmers and consumers alike tend to have difficulties in differentiating rice varieties and determining quality, and are thus exposed to fraudulent behavior by unscrupulous retailers (Lv et al., 2025). To solve these issues, Artificial Intelligence (AI)-based expert systems have been developed to identify rice varieties (Tahsin et al., 2024). However, rice variety recognition is not easy to automate because the number of rice varieties grown worldwide is enormous (Rauf et al., 2022). The uneven distribution of rice grains in particular regions also makes this more difficult. However, research on the automation of rice classification remains limited (Razavi et al., 2024b; Islam et al., 2025b). Conventional evaluation techniques employed in the assessment of rice features to guarantee quality and variety are not only tedious and expensive but also rely on hazardous chemical mixtures (Liu et al., 2025). Consequently, there is a need for automated, efficient, and sustainable methods for rice variety identification (Li et al., 2024). These innovations would transform the process of rice quality assessment, making it more affordable, faster, and more eco-friendly (Alshahrani et al., 2023).

Problem Statement and Objective

Conventional methods often fail to extract reliable features, such as shape and texture, due to variations in environmental conditions, including lighting variations, background noise, and natural overlaps in appearance. These challenges result in inaccurate performance. In addition, the high visual similarity among different rice types complicates the classification process, resulting in high misclassification and low accuracy. To overcome these issues, this research proposes feature extraction methods that efficiently capture variations in shape, color, and texture while reducing the effects of overlapping features. Moreover, Deep Learning (DL) models are employed to enhance the model's ability to distinguish between rice types with subtle visual differences, leading to higher classification accuracy and overall performance.

The main contributions of this research are as follows:

- Integrates a hierarchical residual connection in a pyramidal design to efficiently capture multiscale shape features of rice, preserving both fine-grained local structures and global patterns for robust representation of visually similar varieties
- Applies Sobel-based edge enhancement within the texture branch to highlight the boundary and contour information, improving the model's ability to discriminate subtle variations in surface textures
- Employs an adaptive fusion mechanism to apply attention weighting to concatenated shape and texture features, selectively enhancing discriminative features while suppressing redundant features, thereby enhancing classification accuracy in fine-grained tasks

Literature Review

Alshahrani et al. (2023) introduced the Automated Rice Variety Detection and Classification using Quantum-Inspired Moth Flame Optimizer with DL (ARVDC-QIMFODL) technique. ARVDC-QIMFODL focused on automated identification and classification of distinct types of rice varieties. Feature extraction was performed using a ShuffleNet model and Long Short-Term Memory (LSTM) techniques for rice detection and classification.

Rajalakshmi et al. (2024) suggested a Deep Neural Network (DNN) named RiceSeedNet for rice seed variety identification integrated with conventional image processing to classify local rice seed varieties. To automate the identification of rice seed varieties, a vision-transformer-based architecture was introduced, which achieved higher classification accuracy for both rice grain and seed classification.

Tasci et al. (2023) developed a Quantized Neural Network (QNN) to effectively classify rice varieties and reduce resource usage on edge devices. QNN was better at reducing computational costs and power requirements than numerous DL algorithms. Enhancement of the quantization process enabled efficient AI applications in microcontroller-driven edge devices.

Naik et al. (2024) implemented a Support Vector Machine (SVM) for the classification of rice varieties. In the rice image dataset, 12 morphological features, four shape features, and 90 color features were extracted from the images. An Analysis of Variance (ANOVA) was utilized to select high-rank features, which were then fed into an SVM for classification purposes. SVM effectively constructed an optimal hyperplane that minimized the distance between classes. The extraction of shape enhanced the classification accuracy. Nevertheless, the performance of the SVM was compromised on the rice grain datasets, where inconsistent image quality introduced noise that affected the model's ability to classify subtle grain variations.

Saxena et al. (2022) developed various Machine Learning (ML) algorithms for rice variety classification. The process included data loading, preprocessing, feature scaling using standard scaling, feature selection using Random Forest (RF), and classification using various ML algorithms. Logistic Regression (LR), Decision Tree (DT), SVM, RF, perceptron, K-Nearest Neighbor (KNN), and Gaussian Naïve Bayes (NB) were considered ML classifiers for rice variety classification.

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Agustiono et al. (2025) suggested DENS-INCEP, a transfer learning approach that integrated DenseNet-201 with an Inception module for rice variety classification. DenseNet-201 was utilized as the backbone for feature extraction, while Inception improved the model's ability to capture multiscale shape-related features, which enhanced the classification accuracy. The DENS-INCEP contributed to the Sustainable Development Goals (SDGs) by enhancing security through improved rice production and supply chain stability.

Hanumesh Vaidya et al. (2025) introduced a hybrid Extreme Gradient Boosting with Multi-Layer Perceptron (XGB-MLP) model for rice variety classification. The XGB-MLP was developed to handle class imbalance, thereby providing accurate and fair classification across all rice varieties. This model can be applied to both binary and multi-class classification and can adapt to various datasets and real-time applications due to its versatility.

Although the current models of rice variety classification have demonstrated encouraging performance, several weaknesses remain, such as the lack of scalability to high computational complexity in deep models, the requirement of large-scale pre-training, the failure to provide sufficient flexibility for handcrafted features in different environments, the ineffectiveness of quantized models in retaining fine-grained features, and the sensitivity of SVM-based methods to noisy or unsteady feature extraction. In addition, traditional ML classifiers can fail to generalize between datasets because of environmental differences, and transfer learning models require enormous computational resources and training data.

Model Selection

In this research, a dual-branch CNN architecture was used for feature extraction, which includes PRU and a SEL. PRU provides the capability of learning features in a multi-scale hierarchical fashion, and the Sobel edge layer provides better sensitivity to texture by focusing on edge-related content. This combination ensures the representation of both shape-based and texture-based features for different lighting and environmental conditions. This model balances accuracy, robustness, and computational efficiency, making it a suitable choice for rice variety classification.

Materials and Methods

This manuscript proposes a DB-PRU-SEL to classify rice images. A rice image dataset is used for training and evaluation. The deep learning stage consists of a two-branch CNN: One branch contains a PRU for learning multiscale hierarchical features, and the other includes a SEL for focusing on edge-related structural features. Combining the two branches improves feature representation and classification accuracy. Figure 1 shows the workflow of rice image classification based on the proposed DB-PRU-SEL model.

Dataset

The rice image dataset (Köklü et al., 2021) consists of five distinct varieties of rice commonly refined in Ipsala, Arborio, Basmati, Jasmine, and Karacadag. It consists of a total of 75,000 images, with each variety represented by 15,000 images. These images are in RGB format with a resolution of 250×250 pixels, each capturing a single grain of rice. To avoid identity leakage, all images are shuffled and separated at the grain level, ensuring that no duplicate grain appears among splits. The dataset is divided into 70% for training, 20% for testing, and 10% for validation. The dataset is considered large-scale, with 75,000 images and a balanced class distribution, enabling reliable training and evaluation. Figures 2 and 3 display the class distribution and sample images from the rice image dataset.

Preprocessing

Although the dataset is represented as RGB images with a resolution of 250×250, all inputs are converted to grayscale before being processed by the model. Rice grains have fewer chromatic variations, and their discriminative cues are formed by morphology, contour sharpness, and micro-textures rather than color information. The grayscale conversion minimizes noise in the illumination and eliminates redundant color channels, thereby retaining all the structural information based on intensity required by the PRU and Sobel processes. The original images are used without cropping or padding, and the resulting grayscale images are fed to the shape and texture branches, preserving discriminative information.

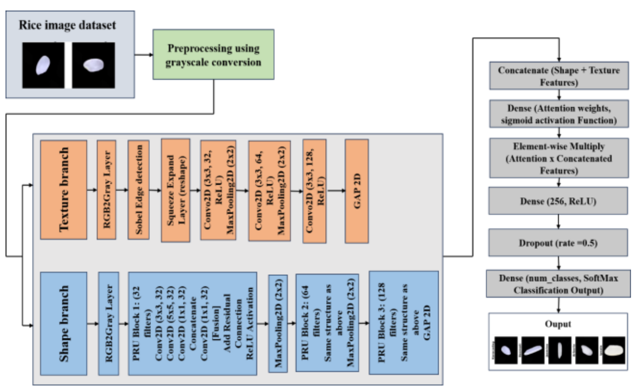

Fig. 1: Workflow of dual-branch framework showing shape and texture feature extraction for rice image classification

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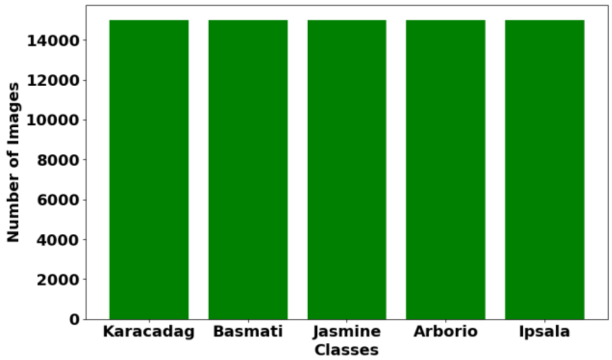

Fig. 2: Class-wise distribution of rice images across five categories within the dataset

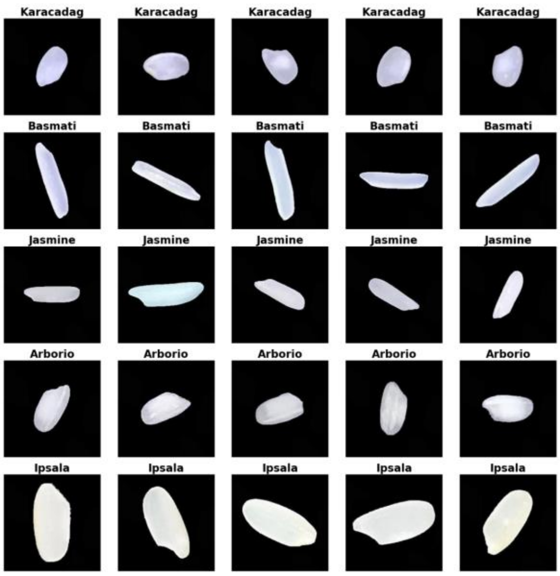

Fig. 3: Rice grain samples from each category included in the image dataset.

Classification

The shape branch is used in the proposed architecture to obtain multiscale structural features without disturbing gradient flow during deep network training. Since residual learning is a proven method to address the problem of vanishing gradients and lack of feature expressiveness, a residual network structure is included in the backbone of this branch. In particular, the identity mapping of the input is applied to the feature maps that are retrieved following a convolution and, therefore, allows reusing features and enhancing representational richness. The shape branch consists of a backbone of PRUs. The PRU consists of three stacked RUs, and dense connections are used between all RUs. The output of the n th RU is a combination of the outputs of all previous RUs, as well as the original input of the first RU. This dense connection strategy ensures that the properties of various scales are simultaneously used, and feature loss is avoided, thereby enhancing gradient propagation.

The novelty of the proposed DB-PRU-SEL lies not only in the use of a dual-branch structure but also in the unique integration and enhancement of its components. Particularly, the PRU provides a multi-scale hierarchical residual structure compared to conventional residual and pyramid networks. The SEL is not only used as static preprocessing but also embedded in the network as a learnable texture enhancement module. Moreover, the model utilizes an attention-based adaptive fusion mechanism, which replaces conventional fixed fusion strategies, providing more discriminative features. Unlike conventional models, where fixed-size convolutional kernels or parallel branches are used, the PRU assumes a pyramidal-shaped design. The initial two RUs use a conventional 3×3 convolution, and the third unit uses a dilated convolution to continually expand the receptive field without spatial resolution loss. The design simultaneously captures both local fine-grain details and larger contextual patterns, which are critical for reliable shape abstraction. Every RU has two convolutional layers, two layers of Batch Normalization (BN), two layers of Rectified Linear Unit (ReLU) activation, and a skip connection. For the input batch $x = (x_1, x_2, \dots, x_m)$, the BN transformation is defined in Equations (1-3):

$$\mu B = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{1}$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu B)^2 \tag{2}$$

$$BN(x_i) = \gamma \frac{x_i - \mu B}{\sqrt{\sigma_B^2 + \epsilon}} + \beta \tag{3}$$

Where μB and σ_B^2 denote the batch mean and variance, γ and β are learnable scaling and shifting parameters, and ϵ is a small constant for numerical stability. By standardizing the distribution of features, the BN layer provides stable training. The nonlinear ReLU activation is then applied to the normalized activations to improve the representation power of the network. The PRU in the shape branch ensures hierarchical multi-scale feature extraction, effective gradient flow, and preservation of shallow and deep structural cues. These extracted features create the shape representation that is subsequently combined with textural information in the parallel branch to enable robust classification. The PRU differs from conventional residual, dilated, or feature pyramid blocks by unifying residual learning, dense connectivity, and pyramidal scaling within a single model. The PRU performs multi-scale processing within one residual using sequential 3×3, 5×5, and dilated convolutions. All scales are integrated using a 1×1 convolution, providing unified multi-scale fusion not present in conventional models. The single-path pyramidal model improves gradient flow, reduces memory, and enhances feature reuse while capturing fine and global morphology in a unified block. To maintain a coherent definition, the PRU is estimated as a three-stage hierarchical residual model, where each residual unit integrates multi-scale kernel operations. Each residual unit applies 3×3, 5×5, and 1×1 convolutions to extract features at various scales, and the final residual unit replaces the 3×3 convolution with a dilated 3×3 convolution to enhance spatial context without causing loss of spatial resolution. The outputs from multi-kernel operations are integrated and compressed by 1×1 fusion, followed by residual skip and nonlinear activation. This ensures that the PRU captures global, mid-level, and fine-grained features within a single pyramidal residual structure.

The texture branch encodes fine-grained and boundary-conscious textural information from the input image. Classical convolutional filters can focus on global features but fail to capture fine changes in the edges. To overcome this weakness, this research used Sobel edge detection as a preprocessing method, which ensures that the texture descriptors are augmented with boundary information prior to convolutional feature learning. The Sobel operator estimates the horizontal and vertical gradients of the input image $I(x, y)$ using two convolution kernels, G_x and G_y, as shown in Equation (4):

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \qquad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{4}$$

The gradients along the x and y directions are estimated as shown in Equation (5):

$$I_x = I * G_x, \quad I_y = I * G_y \tag{5}$$

Where $*$ denotes the convolution operation. The gradient magnitude highlights the edge intensity, as shown in Equation (6):

$$M(x, y) = \sqrt{I_x^2 + I_y^2} \tag{6}$$

The resulting edge maps obtained are fed into the feature extraction pipeline, which passes through a sequence of convolutional layers with ReLU activation and max-pooling. This hierarchical learning process transforms crude edge information into high-level texture embeddings. Finally, a Global Average Pooling (GAP) layer pools the derived texture responses into a feature vector. Sobel edge detection is included so that the texture branch focuses on sharp intensity changes and fine contours, thereby complementing the shape branch. While the shape branch concentrates on global structural patterns, the texture branch emphasizes local boundary information; together they create a more discriminative feature representation for classification.

The DB-PRU-SEL introduces a novel integration of these components in a coordinated dual-branch architecture. Unlike the existing models, the proposed DB-PRU-SEL separates shape learning and boundary-sensitive texture encoding, thereby creating a structural feature for high-similarity rice grains. The PRU provides a unique hierarchical residual pyramid, which captures multi-scale structure, while the Sobel layer performs as a trainable texture encoder rather than a static preprocessing filter. The integration of branches with adaptive attention fusion makes the model functionally distinct from the previous CNN variants. In the proposed model, the features extracted from the shape and texture branches are concatenated to form a unified representation that integrates both structural and textural information. These combined feature vectors are then passed through a dense layer with a sigmoid activation function to produce attention weights, representing the relative importance of different features. The model adaptively recalibrates the feature representation by element-wise multiplication of these attention weights with the concatenated features, thus emphasizing important features and suppressing irrelevant or less informative ones. The refined features are then run through a fully connected dense layer of 256 units with ReLU activation, which increases the nonlinear representation capacity of the network and learns complex decision boundaries. A dropout layer with a rate of 0.3 is applied at the end of this dense layer to prevent overfitting and enhance generalization. The last step involves feeding the refined feature representation into a classification layer with as many neurons as rice classes, where a SoftMax activation function generates class probabilities. The class with the highest probability is assigned as the predicted rice variety. The random seed is set to 42 to ensure consistency and reproducibility in the data splitting process. Pseudocode for the proposed DP-PRU-SEL is provided to enhance reproducibility. Table 1 lists these parameters and their respective values.

Pseudocode

```
FOR each input image:
  1. Input: RGB image of size 250×250.
  2. Preprocessing for both branches:
     a. Convert image to grayscale.
  3. Shape Branch (with PRU):
     a. PRU Block 1:
        i. Input grayscale image
        ii. Apply Conv2D (3×3, 32 filters)
        iii. Apply Conv2D (5×5, 32 filters)
        iv. Apply Conv2D (1×1, 32 filters)
        v. Concatenate the outputs from ii–iv
        vi. Fuse using Conv2D (1×1, 32 filters)
        vii. Add residual connection from input
        viii. Apply ReLU activation
```

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b. Apply 2×2 MaxPooling
c. PRU Block 2:
i. Same as above with 64 filters
d. Apply 2×2 MaxPooling
e. PRU Block 3:
i. Same as above with 128 filters
f. Apply GAP to get a shape-based feature vector
4. Texture Branch:
a. Apply Sobel edge detection on a grayscale image
b. Reshape the Sobel edge map to match Conv2D input
c. Apply 3×3 Conv2D (32 filters, ReLU)
d. Apply 2×2 MaxPooling
e. Apply 3×3 Conv2D (64 filters, ReLU)
f. Apply 2×2 MaxPooling
g. Apply 3×3 Conv2D (128 filters, ReLU)
h. Apply GAP to get a texture-based feature vector
5. Feature Fusion:
a. Concatenate shape and texture feature vectors
b. Pass the concatenated vector through a Dense layer with sigmoid activation
c. Multiply attention weights with the concatenated feature vector (element-wise)
6. Classification Head:
a. Apply a dense layer with 256 units and ReLU activation
b. Apply Dropout (rate = 0.3)
c. Apply a dense layer with units equal to the number of classes and Softmax activation.
7. Output: Class probabilities
END FOR

Table 1: Detailed parameter architecture configuration and values of the proposed DB-PRU-SEL model

Parameter	Value
Loss function	categorical_crossentropy
Epoch	20
Batch size	64
Learning rate	0.0001
Optimizer	adam
Activation function	softmax
Train, test, and validation ratio	70:20:10
Dropout	0.3

Discussion

The proposed DB-PRU-SEL is implemented in Python on a system running Windows 10 OS, with an Intel i5 processor and 16GB RAM. Performance metrics, including accuracy, recall, precision, F1-score, specificity, and AUC, are used to evaluate the model, as presented in Equations (7-11):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (9)$$

$$F1-score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (10)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (11)$$

Here, TN, TP, FN, and FP represent True Negative, True Positive, False Negative, and False Positive, respectively. The evaluation metrics reported in Tables 2 to 4 are estimated using macro averaging, in which precision, recall, and F1-score are calculated for each class independently and then averaged across all classes. The values are derived from predictions on 15,000 test samples, with only minor variations in per-class performance and a macro-average value of 99.87%. The results indicate that the superior performance of the proposed DB-PRU-SEL is due to the multi-scale shape and texture features. The PRU captures structural details, while SEL enhances boundary information and overall discriminative capability. The attention-based fusion refines feature selection, leading to higher accuracy.

Table 2 presents a performance analysis of the proposed DB-PRU-SEL with various classifiers on the rice image dataset. Conventional classifiers such as CNN, DNN, Feed-Forward Neural Network (FFNN), DenseNet, Fully Connected Neural Network (FCNN), MobileViT, ConvNeXt, and CoATNet achieve reasonable results; however, their accuracy, recall, precision, and F1-score are slightly lower because they are less adaptable to fine-grained variation in rice grains.

Table 2: Comparative performance of the proposed DB-PRU-SEL against traditional classifiers on the rice image dataset.

Method	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)	Specificity (%)	AUC (%)
CNN	90.10	90.26	91.23	90.55	89.80	90.35
DNN	92.68	92.91	92.44	92.67	92.39	92.84
FFNN	94.17	93.88	94.63	94.25	94.05	94.33
DenseNet	96.73	96.9	96.48	96.69	96.85	96.78
FCNN	97.42	97.26	97.58	97.41	97.61	97.49
MobileViT	97.95	97.88	98.02	97.95	98.10	98.06
ConvNeXt	98.34	98.27	98.41	98.34	98.45	98.52
CoATNet	98.79	98.72	98.85	98.78	98.90	98.94
DB-PRU-SEL	99.87	99.87	99.87	99.87	99.97	99.99

Table 3: Performance comparison of DB-PRU-SEL with CNN variants incorporating different architectural enhancements on the rice image dataset

Method	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)	Specificity (%)	AUC (%)
CNN	90.10	90.26	91.23	90.55	89.80	90.35
CNN-CBAM	93.70	90.26	91.23	90.55	89.80	94.82
CNN-ASSP	96.60	93.99	94.01	93.98	94.45	96.77
CNN-residual block	97.00	96.69	96.70	96.66	96.55	97.09
CNN-SE	97.93	97.06	97.10	97.08	97.12	98.10
DB-PRU-SEL	99.87	99.87	99.87	99.87	99.97	99.99

Table 4: Ablation study results showing contributions of PRU and SEL components in classification accuracy on the rice image dataset

Method	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)	Specificity (%)	AUC (%)
CNN	90.10	90.26	91.23	90.55	89.80	90.35
DBCNN	96.45	96.42	96.60	96.42	96.51	96.70
DBCNN-SEL	97.84	97.92	97.79	97.85	97.68	97.95
DBCNN-PRU	98.63	98.61	98.69	98.65	98.75	98.80
DB-PRU-SEL	99.87	99.87	99.87	99.87	99.97	99.99

Table 5: Complexity analysis comparing training time, memory usage, and inference time of different models on the rice image dataset

Method	Training time (s)	Memory Usage (MB)	Inference time (s) per image
CNN	557.57	694.62	0.715
CNN-CBAM	542.71	693.57	0.716
CNN-ASSP	427.46	693.56	0.677
CNN-residual block	236.34	741.18	0.630
CNN-SE	345.06	662.20	0.687
DB-PRU-SEL	227.56	601.44	0.530

DenseNet and FCNN show improvement with the addition of dense connections and fully connected layers, but minor misclassifications remain. In contrast, the proposed DB-PRU-SEL model achieves 99.87% accuracy, recall, precision, and F1-score, as well as 99.97% specificity and 99.99% AUC, demonstrating its high capacity for extracting discriminative features and reducing classification errors.

Table 3 depicts the performance analysis of the proposed DB-PRU-SEL and its variants, including CNN, CNN-Convolutional Block Attention Module (CBAM), CNN-Adaptive Spatial-Spectral Pyramid Pooling (CNN-ASSP), CNN-residual block, and CNN-SE. These variants enhance feature representation by incorporating attention modules, residual learning, and squeeze-excitation mechanisms. These models are effective in improving the default CNN and provide significant improvements in performance, particularly in terms of precision and specificity.

Nevertheless, they remain slightly inadequate in capturing complex inter-class similarities. The proposed DB-PRU-SEL has better robustness and generalization in its rice grain classification tasks, with higher accuracy, recall, precision, F1-score, specificity, and AUC of 99.87%, 99.87%, 99.87%, 99.87%, 99.97%, and 99.99%, respectively, on the rice image dataset.

Table 4 illustrates the ablation analysis of the proposed DB-PRU-SEL and its variants, that is, CNN, DBCNN, DBCNN-SEL, and DBCNN-PRU. CNN only provides 90.10% accuracy with low recall, precision, and specificity, thereby indicating that it cannot deal with the complicated dependencies of features. With the use of the DBCNN, feature reuse and representation are enhanced, and the result improves to 96.45% accuracy. The addition of DBCNN-SEL reinforced and maximized discriminative feature extraction to 97.84%. Similarly, DBCNN-PRU integration has an accuracy of 98.63%, which indicates that sequential dependency modeling is enhanced by the use of recurrent processing. However, the proposed DB-PRU-SEL outperformed all other variants and attained the highest accuracy, recall, precision, and F1-score of 99.87%, as well as a specificity and AUC of 99.97%, indicating that it has a better capacity to achieve fine-grained details and reduce classification errors.

Table 5 demonstrates the complexities of various CNN-based models in terms of training time, memory usage, and inference time. The minimum training time of 557.57s and comparatively large memory consumption of 694.62MB are associated with the smallest inference time of 0.715s per image for the baseline CNN. CNN-CBAM, CNN-ASSP, CNN-residual block, and CNN-SE variants enhance computational efficiency through additive attention and residual mechanisms, although they do not provide significant training or inference overhead reductions. To illustrate, the CNN-residual block significantly decreases the inference time by 0.630s, whereas CNN-SE is efficient in memory utilization. When compared to this, the proposed DB-PRU-SEL has

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a better trade-off due to its training time of 227.56s, memory of 601.44 MB, and inference time of 0.530s per image, thereby ensuring that the model is computationally efficient with a high classification performance.

Table 6 presents the statistical analysis and standard deviation values of the various classifiers based on their significance levels. The proposed algorithm has the smallest significance value, which indicates that it has a greater capability to distinguish small-scale grains and reduce the probability of classification mistakes. The minimum p-value of 0.014 represents the proposed approach, which identifies meaningful differences better than conventional classifiers. This means that the method is statistically more reliable for differentiating the classes of rice grains. The confidence interval is 99.76%-99.98%, which implies that the method has less uncertainty in prediction. This range shows that the model is consistent in its accuracy when applied to various datasets and test samples, whereas other approaches have wider ranges. The standard deviation of ±0.11 in the DB-PRU-SEL model is the smallest; therefore, it is exceptionally robust. This small change indicates that the model always draws optimum solutions in various experiments. The Wilcoxon signed-rank test is conducted to estimate statistical significance between the proposed and existing methods. The attained p-values (<0.05) ensure that the enhancements are statistically significant and not due to random variation. The statistical validation is utilized to show that the performance improvements of the proposed DB-PRU-SEL are reliable and not due to random chance. In this research, three statistical measures are considered: P-value, confidence interval, and standard deviation. The confidence interval provides higher reliability and stability across different samples, thereby ensuring consistent performance. The standard deviation estimates the variation in performance across multiple experiments. A lower standard deviation denotes that the model produces better and more consistent results, thereby ensuring robustness.

Table 7 visualizes the K-fold cross-validation of the proposed DB-PRU-SEL model using the rice image data to evaluate its performance with different fold configurations and assess its stability. The results denote that the model maintains high performance among all K-values, with only minor deviations in accuracy, recall, precision, and F1-score. Among the evaluated K-values, K = 5 achieves stable and balanced results with 99.87% consistency in all evaluation metrics, thereby mitigating the risk of overfitting and underfitting variance. The overall high performance of the remaining K-values also ensures the validity and higher test reliability of DB-PRU-SEL, which shows that it is reliable in various validation conditions when classifying rice grains.

Table 8 visualizes the performance of the proposed DB-PRU-SEL model for various rice grain types.

Table 6: Statistical and deviation analysis validating the significance and consistency of DB-PRU-SEL performance on the rice image dataset

Method	P-value	Confidence Interval (%)	Standard deviation
CNN	0.029	89.57 – 90.63	±0.53
DNN	0.025	92.21 – 93.15	±0.47
FFNN	0.019	93.75 – 94.59	±0.42
DenseNet	0.028	96.37 – 97.09	±0.36
FCNN	0.021	97.09 – 97.75	±0.33
MobileViT	0.018	97.62 – 98.28	±0.33
ConvNeXt	0.016	98.05 – 98.63	±0.29
CoATNet	0.015	98.52 – 99.06	±0.27
DB-PRU-SEL	0.014	99.76 – 99.98	±0.11

Table 7: Cross-validation results of DB-PRU-SEL demonstrating stability across different K-fold validations on the rice image dataset

K-values	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
2	99.62	99.64	99.59	99.61
3	99.74	99.76	99.72	99.74
5	99.87	99.87	99.87	99.87
6	99.71	99.72	99.7	99.71
7	99.80	99.81	99.78	99.79

Table 8: Class-wise performance of DB-PRU-SEL across five rice grain varieties with high accuracy

Classes	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	AUC (%)
Karacadag	99.40	99.93	99.67	99.85	99.99
Basmati	100	100	100	100	100
Jasmine	100	100	100	100	100
Arborio	99.93	99.40	99.67	99.98	99.99
Ipsala	100	100	100	100	100
Average	99.87	99.87	99.87	99.97	99.99

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The findings ensure that each variety is categorized by precision, recall, and F1-score, with high specificity and AUC. This consistency in all categories ensures that the model is robust in processing small-scale differences to provide consistent performance with no bias toward a particular class.

The results of the qualitative classification of the proposed DB-PRU-SEL model for the rice grain samples of different varieties are displayed in Figure 4. The findings demonstrate the ability of the model to elicit discriminative morphological attributes, such as the sharpness of contours, elongation of grains, and surface attributes. The predictions are also resistant to external factors and remain consistent even though the grain orientation and illumination vary. This uncommon misclassification also shows how difficult it is to maintain inter-class similarity, although consistency is present in the case of multi-scale spatial features, sequential dependencies, and channel-wise adaptivity to recognize fine-grained rice varieties.

Figure 5(a) displays the training and validation accuracy curves based on epochs. The model is characterized by a rapid increase in accuracy during the early epochs, converging toward nearly perfect accuracy. The training and validation accuracies are also stable with little variation, which demonstrates that the proposed model has a high degree of generalization. The training and validation loss curves are shown in Figure 5(b). The values of the losses decreased drastically in the initial epochs and slowly stabilized at lower values as the training progressed. The proximity of both training and validation losses shows that the model is an effective way to learn discriminative features, making it stable with unobserved samples. This gradual reduction in loss is another indication of the stability and strength of the proposed approach.

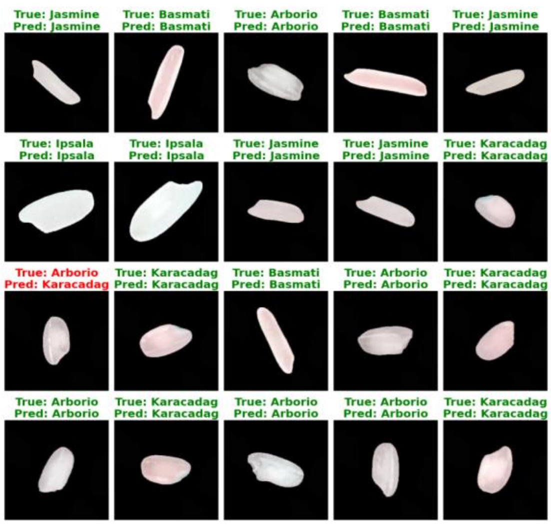

Fig. 4: Qualitative classification results showing DB-PRU-SEL's ability to extract discriminative morphological features

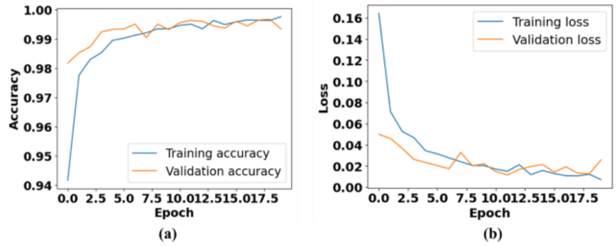

Fig. 5: Performance of DB-PRU-SEL: (a) Training-validation accuracy, (b) Training-validation loss showing convergence stability

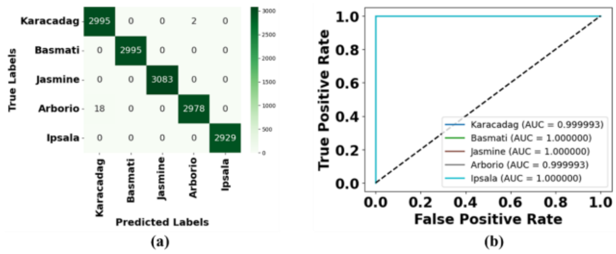

Fig. 6: Classification performance of DB-PRU-SEL: (a) Confusion matrix, (b) ROC curves with AUC values

The confusion matrix of the DB-PRU-SEL model using the rice image dataset is shown in Figure 6(a). The classifier recognizes all five types of rice with high accuracy and a small number of misclassifications. For example, Basmati, Jasmine, and Ipsala classes are perfectly classified, whereas some confusion is observed with Karacadag and Arborio because of their similar appearance characteristics. This demonstrates that the model can be used to achieve high levels of reliability in class separation and to handle subtle interclass similarities. Figure 6(b) presents the Receiver Operating Characteristic (ROC) curves and AUC values for each class. The AUC values of all rice classes are close to 1, indicating the high separability of the positive and negative samples. A high level of discriminative performance is also observed even in visually similar classes, which indicates the strength of the model. The general ROC findings demonstrate the efficiency of the model in reducing false positives and providing consistent classification performance for different rice varieties. This confusion matrix is estimated on the 20% test set that contains approximately 3,000 samples per class, ensuring balanced classes and reliable evaluation of the model performance. The ROC analysis denotes an AUC value close to 1.0. For certain classes, such as Basmati, Jasmine, and Ipsala, it achieves better classification with no FP or FN, resulting in an ROC curve and AUC of 1.0.

The classification report in Figure 7 displays the model performance on the test set, which includes 15,000 samples. Every rice variety has a support of approximately 2,900-3,000 images, ensuring balanced evaluation. All the classes attained near-perfect precision, recall, and F1-score, thereby denoting reliable predictions among similar grain types.

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	precision	recall	f1-score	support
Karacadag	0.994026	0.999333	0.996672	2997
Basmati	1.000000	1.000000	1.000000	2995
Jasmine	1.000000	1.000000	1.000000	3083
Arborio	0.999329	0.993992	0.996653	2996
Ipsala	1.000000	1.000000	1.000000	2929
accuracy			0.998667	15000
macro avg	0.998671	0.998665	0.998665	15000
weighted avg	0.998672	0.998667	0.998667	15000

Fig. 7: Class-wise evaluation showing per-class precision, recall, F1-score, and corresponding support counts

Comparative Analysis

A comparative analysis of the proposed DB-PRU-SEL model with other existing approaches using the rice image dataset is presented in Table 9. It is compared to the proposed model, ARVDC-QIMFODL (Alshahrani et al., 2023); RiceSeedNet (Rajalakshmi et al., 2024); QNN (Tasci et al., 2023); and ANOVA-SVM (Naik et al., 2024). The proposed DB-PRU-SEL model, with the same data size of 75,000 images, achieved the highest accuracy of 99.87% and the same value of 99.87% for recall, precision, and F1-score. This high performance shows the ability of the model to balance classification across all evaluation measures, as compared to the competing methods that are less stable and lack in-depth validation. Due to the combination of PRU and SEL mechanisms in the proposed model, the multilevel feature representation and efficient separation of fine-grained variations in rice grains allow the reduction of bias and error in classification. Thus, it ensures that the DB-PRU-SEL model is more effective than the existing techniques and is considered a reliable, precise, and generalizable model for classifying rice grains.

Research Implications

The findings of this manuscript have implications for rice variety classification and for the broader use of dual-branch DL models. The proposed DB-PRU-SEL incorporates a PRU to generate a shape representation and an SEL to provide texture, enhancing accuracy and efficiency in rice variety classification. The most important research implications are as follows:

(1) Improved multi-scale feature learning: The use of PRUs has shown that dense hierarchical connections are effective at preserving fine-scale shape information and global structural information, thereby providing multi-scale features that are learned in other agricultural vision tasks
(2) Enhanced robustness to visual variability: Sobel edge integration ensures resistance to shifts in illumination, grain orientation, and environmental noise, which is important in the field deployment of imaging systems in which imaging conditions are not controlled
(3) Attention-guided feature fusion: The use of attention-based recalibration provides a model in which feature-level weighting increases discriminative ability, providing a transferable approach to other fields requiring fine-grained classification
(4) Stability across heterogeneous classes: All five classes of rice are perfectly classified, demonstrating that DB-PRU-SEL generalizes well to other classes with subtle visual differences. Therefore, it may be replicable for other staple crops
(5) Scalability and computational efficiency: The balance between less training time, limited memory usage, and high accuracy demonstrates that with lightweight design improvements, a dual-branch CNN can be effectively deployed in a large agricultural practice
(6) Broader applicability beyond rice: DB-PRU-SEL provides a way to apply shape-texture combined deep models to other agricultural and food-quality assessment tasks, providing a strong future direction in smart-farming solutions

Table 9: Comparative analysis highlighting DB-PRU-SEL superiority over existing methods on the rice image dataset

Method	Number of samples	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
ARVDC-QIMFODL (Alshahrani et al., 2023)	5000	99.55	98.85	98.85	98.84
RiceSeedNet (Rajalakshmi et al., 2024)	8000	99	99	99	99
Quantized Neural Networks (Tasci et al., 2023)	75000	99.8	NA	NA	NA
ANOVA-SVM (Naik et al., 2024)	75000	99.81	NA	NA	NA
DB-PRU-SEL	75000	99.87	99.87	99.87	99.87
	5000	99.70	99.60	99.62	99.61
	8000	99.78	99.72	99.74	99.73

Conclusion

In this research, a DB-PRU-SEL was proposed to classify rice varieties. This model used a dual-branch architecture, in which the shape branch used PRU to hierarchically encode multiscale structural changes of rice grains, and the texture branch used SEL and convolutional layers to emphasize the grain boundaries and surface details in the image. This supplemental architecture allowed the network to overcome the limitations of traditional handcrafted methods and conventional DL algorithms, which make it challenging to distinguish between visually similar images due to variations in lighting conditions and environmental noise. Moreover, the addition of an attention-based feature fusion system increased the discriminative capabilities of the fused features; thus, the network focused on the most pertinent attributes during classification. The validation on rice images showed that DB-PRU-SEL performed better than the CNN baselines and state-of-the-art variants, with an accuracy of 99.87% and an AUC of 99.99%. The DB-PRU-SEL demonstrated reduced training time and memory usage, thereby making it computationally efficient and suitable for scalable deployment. Future work will focus on improving feature representation and generalization ability to enhance adaptability and efficiency for wider plant species classification.

Notation List

Notations	Descriptions
μB	Batch mean
σ_B^2	Batch variance
γ	Learnable scale parameter
β	Learnable shift parameter
ϵ	Stability term
$I(x, y)$	Input image
G_x and G_y	Convolution kernels
$*$	Convolution operation
TN	True Negative
TP	True Positive
FN	False Negative
FP	False Positive

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Author's Contributions

M Pradeep: Was responsible for conceptualization, methodology, data collection, and initial drafting of the manuscript.

M Siddappa: Contributed to the analysis, validation, and critical revision of the manuscript. Both authors reviewed and approved the final version of the manuscript for publication.

Ethics

The authors affirm that this manuscript does not involve human participants, animals, or sensitive data and therefore does not require ethical approval. The authors declare that there are no ethical concerns associated with the publication of this work.

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