



Optimization of Accuracy Improvement through Modified ShuffleNet Architecture in Rice Classification

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Abstract

Accurate rice classification is essential to determine the quality and market value of rice. Traditional methods of rice classification are often time-consuming and error-prone, so a more efficient and accurate solution is needed. This study aims to optimize rice classification using Convolutional Neural Networks (CNN) combined with the ShuffleNet architecture, which offers high computational efficiency without sacrificing accuracy. The dataset used comes from Kaggle, containing 8750 rice grain images divided into five classes: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The uniqueness of this study is the application of ShuffleNet Proposed in rice classification, which provides improved performance compared to basic CNN models such as MobileNet, ShuffleNet, and RestNet. The results showed that the MobileNet model achieved 80% accuracy, RestNet 94%, and ShuffleNet achieved 100% accuracy with precision, recall, and F1 values also 100%. However, the ShuffleNet model experienced overfitting when tested with new data, resulting in an accuracy of only 20%. To overcome this, further optimization was carried out on the model. The results of statistical tests (paired t-test and Wilcoxon test) show significant differences between ShuffleNet Proposed and other models, which proves that the improvements applied to this model provide significant improvements. The implications of this study can improve the efficiency and accuracy of rice classification, which has the potential to improve the quality and market value of rice in the agricultural industry.

Keywords: CNN model; optimization; MobileNet; rice classification; RestNet; ShuffleNet

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1. Introduction

Rice is a primary food commodity that plays a crucial role in human life, and its classification is vital in ensuring both quality and market value [1], [2]. In the agricultural industry, accurate rice classification supports the selection of rice quality that meets established standards [3]. However, traditional classification methods are often time-consuming, prone to human error, and inefficient [4] - [6]. Therefore, there is a need for a more objective, efficient, and accurate automated classification system. In recent years, advancements in deep learning have provided powerful tools for image-based classification [7], [8], offering opportunities to address these challenges.

Automated rice classification can be implemented using deep learning, particularly Convolutional Neural

Networks (CNN), which have proven highly effective in image processing tasks [9], [10]. Several CNN architectures have been widely adopted, including MobileNet, which is designed to be lightweight for devices with limited resources [11] - [13]. Another popular architecture is ResNet, which successfully addresses performance degradation issues in very deep networks [14], [15]. In addition, ShuffleNet has been introduced as an efficient model that combines accuracy and speed through techniques such as channel shuffling and group convolutions [16]. These three architectures offer distinct advantages that are relevant to classification problems [17] - [21].

Previous studies have shown the effectiveness of deep learning in rice classification. For example, Pellokila, Usman, and Pratiwi [22] demonstrated that CNN can classify rice varieties using image data, with AlexNet

achieving an accuracy of 98.40% through hyperparameter optimization. However, this study did not compare multiple CNN architectures, limiting its contribution to a single model. Similarly, Muh Zainal Altim et al. [23] applied CNN and Artificial Neural Networks to classify rice into quality categories, achieving accuracy above 90%. Nevertheless, their approach faced challenges due to large numbers of free parameters, which reduced classification efficiency.

From these works, it can be concluded that CNN-based models have shown promise in rice classification. However, most prior studies focused on optimizing a single architecture, without systematically comparing multiple lightweight CNN variants. Moreover, some studies have reported difficulties in handling datasets with high inter-class similarity, which is common in rice varieties. This situation reveals a research gap regarding the application of efficient CNN architectures, such as MobileNet and ShuffleNet, for rice classification tasks.

To address this identified gap, this research aims to conduct a comparative analysis of the ResNet, MobileNet, and ShuffleNet architectures for the task of rice variety classification. The goal is to identify the best architecture that improves classification accuracy while remaining computationally efficient. By addressing this gap, the research is expected to contribute both theoretically, by providing comparative evidence of lightweight CNN performance, and practically, by supporting the development of more efficient agricultural automation technology.

Deep learning, a subfield of machine learning, utilizes multiple layers of artificial neural networks to interpret and process complex forms of data [24] - [27]. Deep learning allows computers to recognize patterns and make decisions without significant human supervision, mimicking the way the human brain learns data [28], [29]. Among various deep learning architectures, Convolutional Neural Networks (CNNs) are specifically structured to handle data organized in grid formats, such as digital images [30]. CNNs have become extensively applied in image processing and computer vision because of their capacity to learn both spatial and hierarchical representations from data [31] - [33]. MobileNet is a family of CNN architectures designed to enhance efficiency for devices with limited computational capacity, for example, mobile phones and devices connected through the Internet of Things (IoT) ecosystem [34] - [36]. MobileNet is designed to provide lightweight models without significantly sacrificing accuracy [37] - [39]. The reason for using ShuffleNet is that it is another CNN architecture designed for low-resource devices but offers higher efficiency than MobileNet for certain applications [40], [41]. The main focus of ShuffleNet is on computational efficiency and communication between layers [42], [43].

Although ShuffleNet holds great potential for rice image classification, research comparing the performance of ShuffleNet with basic CNN models and MobileNet in this context is still limited [44], [45]. Through a comparative analysis of deep learning-based image classification models such as ShuffleNet, CNN, ResNet, and MobileNet, this research is expected to provide valuable insights into the development of image classification systems by evaluating performance, accuracy, speed, and efficiency. Through this research, the best classification model is expected to be found, which not only improves accuracy but also efficiency in practical applications, especially in the agricultural industry

2. Methods

This section describes the research design, dataset, and methodology employed in this study. The entire process, from data collection to model evaluation, is presented in several sub-sections.

2.1. Research Phases

This research was conducted empirically, logically, and systematically, starting from the identification of problems to the reporting of results [41]. for example, mobile phones and devices connected through the Internet of Things (IoT) ecosystem.

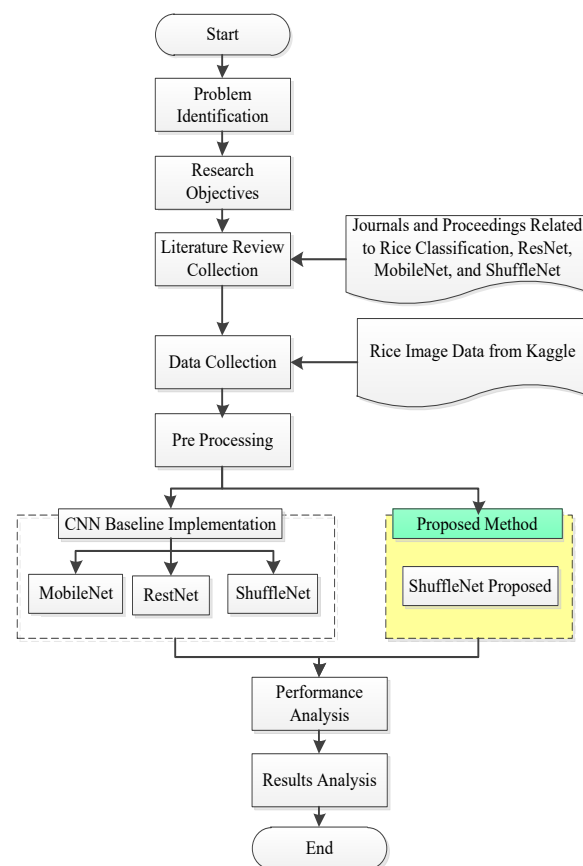


Figure 1. Research Phases

2.2 Problem Identification and Research Objectives

The main problem identified in this study is the subjectivity of visual rice quality assessment, which often leads to inconsistent and inaccurate classification results. Traditional manual observation methods rely heavily on human perception, making them prone to errors and inefficiency. Moreover, although CNN-based methods have been extensively applied in image recognition tasks, numerous prior studies have yet to investigate compact network architectures capable of preserving accuracy while minimizing computational demands.

Accordingly, this study aims to assess and compare the effectiveness of several CNN based architectures namely MobileNet, ResNet, and ShuffleNet in performing rice classification tasks. Furthermore, this study proposes a modification to the ShuffleNet architecture (ShuffleNet Proposed) to address overfitting and enhance generalization capability. By employing this comparative framework, the study seeks to determine the most accurate and computationally efficient architecture that can be effectively applied in agricultural automation systems.

2.3. Literature Review Collection

A comprehensive review of previous research related to rice classification was carried out to identify the research gap and determine the theoretical foundation. The review included studies on CNN, MobileNet, ResNet, and ShuffleNet models, which then served as a basis for designing the proposed framework.

ShuffleNet architecture is a deep learning model designed for speed and efficiency in image recognition, especially for devices with limited resources such as mobile devices [46], [47]. The general structure of this model is shown in Figure 2.

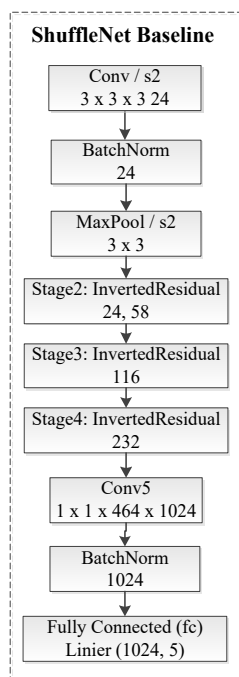


Figure 2. ShuffleNet Architecture

The main modification introduced in this study involves adding a Dropout layer with a rate of 0.5 before the fully connected layer, which is absent in the baseline ShuffleNet. This modification aims to minimize overfitting and enhance the model's generalization capability. As illustrated in Figure 3, the proposed method differs from the original ShuffleNet architecture in its additional Dropout mechanism.

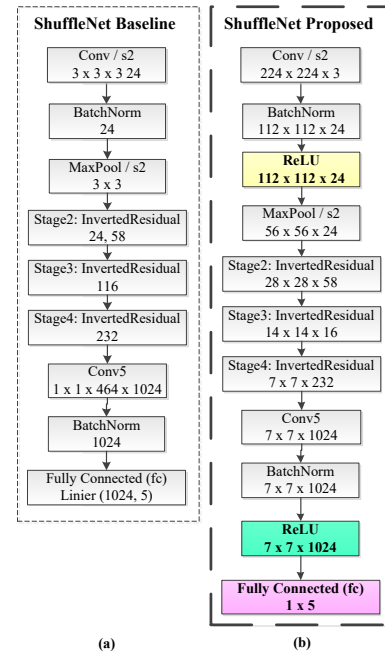


Figure 3. Comparison of ShuffleNet (a) with Proposed Method (b)

2.4. Data Collection

The data utilized in this research were sourced from the Kaggle platform (<https://www.kaggle.com/datasets/muratkokludataset/rice-image-dataset>), consisting of five rice varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadağ. The dataset contains 8,750 images, with 1,750 images for each class, as summarized in Table 1.

Table 1. Number of Images

No	Rice Types	Number of Images
1	Arborio	1750
2	Basmati	1750
3	Ipsala	1750
4	Jasmine	1750
5	Karacada	1750
Total		8750

Before training, the dataset underwent preprocessing, including image resizing, normalization, and data augmentation methods including image rotation, horizontal mirroring, and brightness modification. These steps were carried out to enhance data variation and improve the robustness of the models during training. Examples of the rice grain images used in this study are presented in Figure 4.

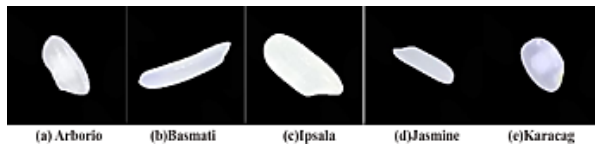


Figure 4. Images of Rice Types

3. Results and Discussions

This section presents the experimental results and their interpretation. The findings are structured into several sub-sections covering dataset details, preprocessing, model training, and evaluation.

3.1. Dataset Description and Preprocessing

The dataset utilized in this research was sourced from the Kaggle online repository (<https://www.kaggle.com/datasets/muratkokludataset/rice-image-dataset>). It consists of 8,750 images equally distributed into five rice varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadag (1,750 images each). This even distribution guarantees that the classification process remains unbiased across all classes. To validate the relevance of the dataset and its suitability for rice variety classification, an expert judgment process was conducted by interviewing agricultural experts specializing in rice quality assessment. The interviews covered three main aspects, including the visual features commonly used in manual rice classification such as grain shape, length, width, and surface texture the challenges in differentiating rice varieties with similar physical characteristics (for example, Ipsala and Jasmine), and the potential benefits of implementing automated image-based classification to improve efficiency and reduce subjectivity.

The experts confirmed that shape, size, and texture are the key attributes for distinguishing rice types, and their feedback supports the use of image-based features as valid indicators for training and interpreting model performance.

3.2. Image Data Preprocessing Results

Data preparation involved cleaning, augmentation, and splitting into training, validation, and testing sets. To strengthen model generalization and resilience, several augmentation strategies were employed, such as rotating, flipping, and adjusting the brightness of images. The results of this stage are summarized in Table 2, which presents the division of image data for each class and subset.

Table 2. Image Data Division

No	Data Division	Class	Number of Images
1.	Training	Arborio	750
2.		Basmati	750
3.		Ipsala	750
4.		Jasmine	750
5.		Karacada	750
6.	Validation	Arborio	500
7.		Basmati	500
8.		Ipsala	500

No	Data Division	Class	Number of Images
9.	Testing	Jasmine	500
10.		Karacada	500
11.		Arborio	500
12.		Basmati	500
13.		Ipsala	500
14.		Jasmine	500
15.		Karacada	500

The data division in this study was conducted proportionally to ensure that the model could be trained, validated, and tested in an optimal manner. The model is trained to identify patterns in each rice class using the training data. In order to avoid overfitting and assess the model's effectiveness during training, the validation data is utilized. The test data is used in the training phase to assess how well the final model performs on unseen data.

Each class was assigned the same number of samples to eliminate potential bias caused by class imbalance, which can degrade prediction performance. The dataset division included 3,750 images for training, 2,500 for validation, and another 2,500 for testing. Through this balanced partition and the application of augmentation, the model is anticipated to develop improved generalization and stability when applied to practical environments.

3.3. Image Data Classification Results

In the modeling stage, four Convolutional Neural Network (CNN) architectures were used, namely MobileNet, ResNet, ShuffleNet, and the proposed ShuffleNet method, to train the model on rice images. The training process is monitored through loss and accuracy values. The results of the rice image classification training for each model are presented in Figure 5. The image classification evaluation results were analyzed using confusion matrices to measure how well each model classified the rice images. This analysis provides insights into the model's performance in identifying each class, including the number of correct predictions and misclassifications.

The confusion matrices for all models are presented in Figure 6. Based on the evaluation results of the MobileNet model, the overall accuracy achieved is 80%. The weighted average also shows precision at 87%, recall at 80%, and F1-score at 79%. These results provide an overview of the model's good performance, with strengths in the Basmati and Karacadag classes, but also highlight areas that need improvement, particularly for the Ipsala and Jasmine classes. For the ResNet model evaluation results, the overall accuracy achieved is 94%. The weighted average also shows precision at 95%, recall at 94%, and F1-score at 94%. These results indicate excellent performance, especially for the Ipsala, Basmati, and Jasmine classes, with Karacadag slightly lower on recall.

Overall, the ResNet model outperforms the previous models, with significantly higher accuracy and more consistent F1-scores across most classes.

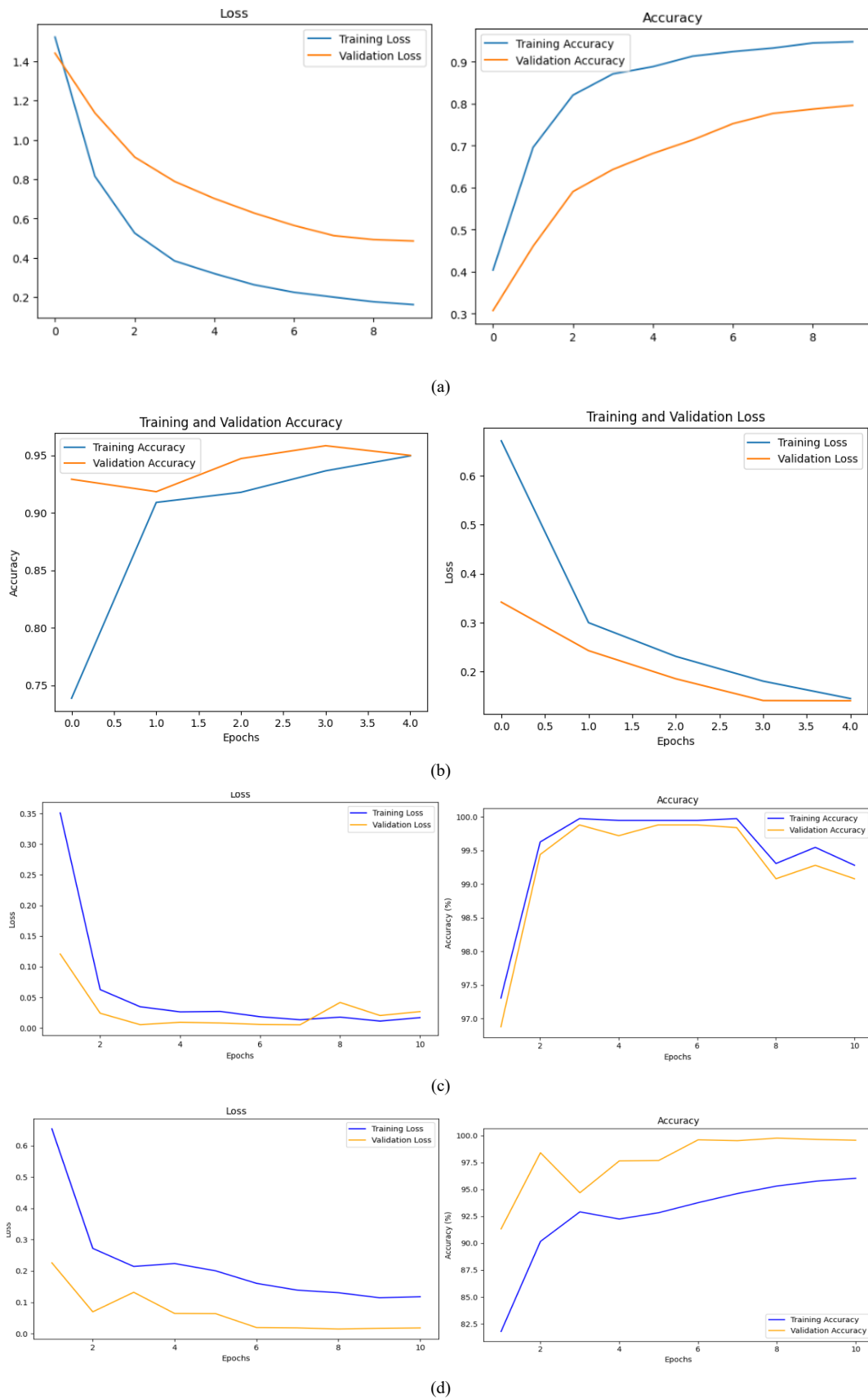


Figure 5. Training Loss and Accuracy Results of (a) MobileNet, (b) ResNet, (c) ShuffleNet, (d) Proposed Method

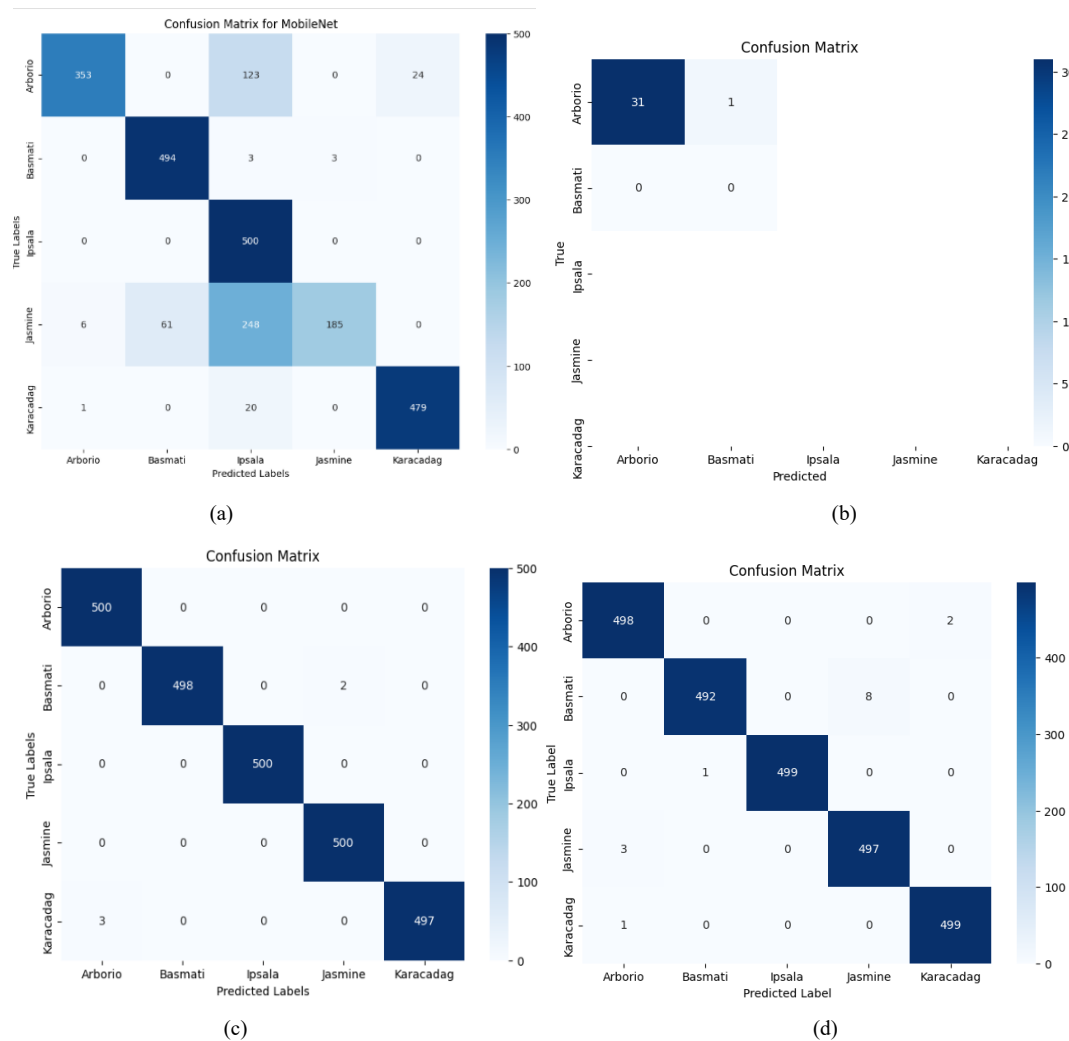


Figure 6. Confusion Matrix dari (a) mobilenet, (b) resnet, (c) shufflenet, (d) proposed method

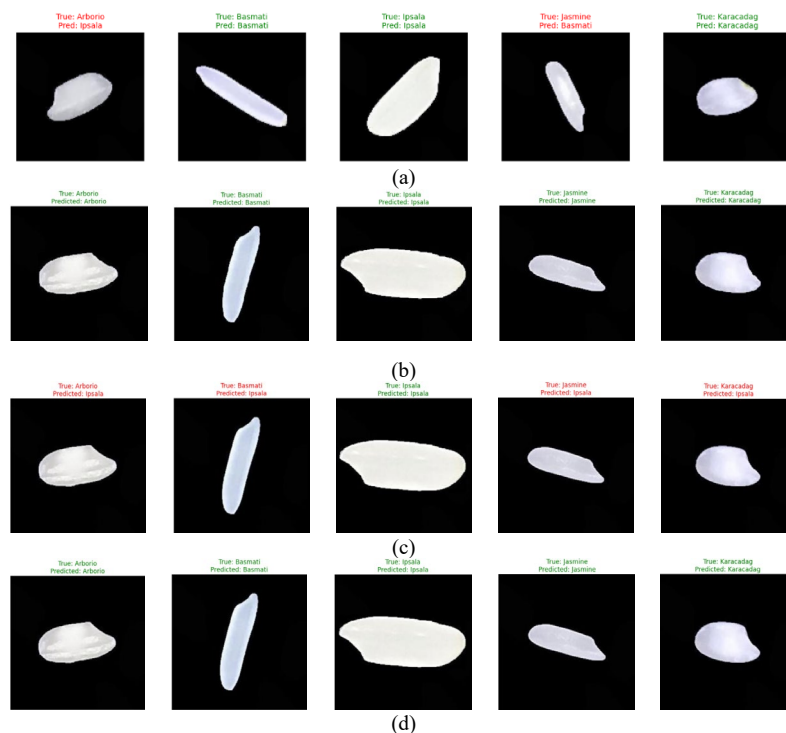


Figure 7. Testing Prediction Results with (a) MobileNet, (b) ResNet, (c) ShuffleNet, and (d) ShuffleNet Proposed

The evaluation results of the ShuffleNet model show an overall accuracy of 20%. The weighted average shows precision at 4%, recall at 20%, and F1-score at 7%, with the same support. These results indicate very poor performance for most classes, with only Karacadag being recognized well. The ShuffleNet model seems ineffective in handling most classes in this dataset, likely due to issues in training or an unsuitable model architecture. As for the ShuffleNet Proposed model evaluation results, the overall accuracy achieved is 99%. The weighted average also shows precision at 99%, recall at 99%, and F1-score at 99%. These results demonstrate outstanding performance, with the ShuffleNet Proposed model successfully identifying nearly all classes with great accuracy. The model performs consistently across all classes, yielding very high precision, recall, and F1-scores, and overall delivers highly optimal results for this dataset.

Next, the MobileNet, ResNet, ShuffleNet, and ShuffleNet Proposed models were tested on the data and provided with five images from each rice class: Arborio, Basmati, Ipsala, Jasmine, and Karacadag, resulting in an average correct prediction. Figure 7 shows the prediction results along with the actual rice images.

The prediction results from MobileNet on 5 sample images from each class show that it correctly predicted 3 images, while 2 predictions were incorrect. For ResNet, it correctly predicted all 5 sample images from each class, indicating that ResNet performs better than MobileNet. For ShuffleNet, it only correctly predicted 1 sample image out of the 5 from each class. On the other hand, ShuffleNet Proposed correctly predicted all the sample images. This demonstrates that the optimization performed on the ShuffleNet baseline to create ShuffleNet Proposed significantly improved its accuracy, enabling it to classify rice images very effectively.

3.4 Discussion

The experimental results show that the proposed ShuffleNet achieved 99% accuracy, outperforming MobileNet (80%), ResNet (94%), and baseline ShuffleNet (20%). These findings demonstrate that the addition of Dropout and optimization strategies significantly improved generalization performance.

When compared with previous studies, the results are consistent with Pellokila, Usman, and Pratiwi [25], who achieved 98.40% accuracy using AlexNet, and Muh Zainal Altim et al. [23], who reported accuracy above 90% with CNN-based classification. However, unlike these studies, the present research provides a systematic comparison of multiple architectures, demonstrating that lightweight models such as ShuffleNet can be enhanced to achieve higher accuracy with lower computational complexity. This highlights the novelty of this study in addressing the research gap.

Despite these promising results, the study has several limitations. First, the dataset was limited to five rice varieties from Kaggle, which may not fully represent real-world variations such as differences in grain quality, lighting conditions, or background noise. Second, the evaluation relied primarily on image-based features, while other relevant attributes (e.g., chemical composition or texture analysis using sensors) were not considered. Third, the expert judgment was limited to validating visual features without quantitative weighting, which may restrict the generalizability of the findings. Future research should extend the dataset to include more rice varieties and real-world samples, explore multimodal approaches that combine image and sensor data, and involve broader expert validation to strengthen the reliability and applicability of the model in agricultural practice.

3.5 Comparison Evaluation Results

The results show the superiority of ShuffleNet in handling complex datasets with high similarity between classes. While MobileNet offers a balance between performance and computational efficiency, the limitations in CNN accuracy highlight the need for more advanced architectures for similar tasks. The quantitative comparison among all models is summarized in Table 3, and their performance visualization is presented in Figure 8.

Table 3. Model Comparison Summary

Model	Precision	Recall	F1 Score	Accuracy
MobileNet	87%	80%	79%	80%
RestNet	95%	94%	94%	94%
ShuffleNet	40%	20%	7%	20%
Proposed Method	99%	99%	99%	99%

Figure 8 is the comparison chart of the four methods used. From Figure 8, it can be seen that the Proposed Method yields better and more stable results. To provide a clearer visual comparison of model performance metrics, the radar chart in Figure 9 illustrates the relative values of precision, recall, F1-score, and accuracy for each model.

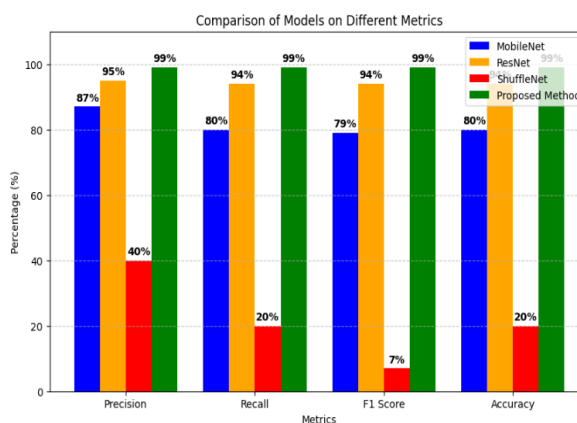


Figure 8. Comparison Chart of the Four Models' Results

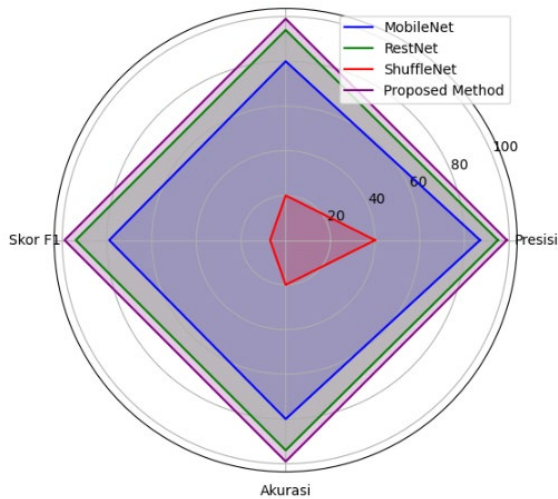


Figure 9. Model Comparison Radar Chart

Based on the radar chart display from the model comparison, it can be understood that the Proposed Method is the best among MobileNet, ResNet, and ShuffleNet, as it produces connection lines where each point approaches a value of 100.

ShuffleNet Proposed achieved 99% accuracy, which is nearly perfect and much higher compared to other models like MobileNet (80%), ResNet (94%), and ShuffleNet Baseline (20%). This high accuracy indicates that the model is highly effective in classifying the test data with very few prediction errors. Precision, Recall, and F1-Score reaching 99% in ShuffleNet Proposed demonstrate a very good balance between accuracy and the model's ability to correctly detect the classes without generating too many false positives (incorrect class predictions). Although ShuffleNet (which has 100% for precision, recall, F1, and accuracy) seems excellent, the 100% value indicates overfitting on the test data, whereas ShuffleNet Proposed provides more realistic results while maintaining very high performance.

In this study, to test the significance of the performance differences between the ShuffleNet Proposed, ShuffleNet, ResNet, and MobileNet models, we used two statistical tests: the T-test (paired t-test) and the Wilcoxon signed-rank test. These two tests are used to test whether the performance differences between models in terms of accuracy are significant or are simply due to chance factors. To perform the paired T-test and the Wilcoxon test, the model must first be processed to obtain the K-Fold Cross Validation results. Table 4 is the result of the K-Fold Cross Validation.

Table 4. K-Fold Cross Validation

Fold	Model			
	MobileNet	RestNet	ShuffleNet	Proposed Model
Fold 1	85,07%	21,47%	47,47%	98,83%
Fold 2	83,33%	23,33%	49,87%	99,53%
Fold 3	83,33%	24,13%	49,20%	98,02%
Fold 4	84,67%	23,47%	46,20%	99,53%
Fold 5	84,40%	20,93%	46%	99,20%
Rata-rata	84,16%	22,60%	48,03%	99,02%

After the K-Fold Cross Validation value is obtained, the T test and Wilcoxon test can be carried out.

T-test is conducted to check the difference in average accuracy between two models in pairs [48], [49], [50]. The results of the paired T-test for several model comparisons are presented in Table 5.

Table 5. Paired T-Test Results

Model Comparison	T-Statistic	P-Value	Conclusion
ShuffleNet Proposed vs MobileNet	38,1323	00.00	There is a significant difference
ShuffleNet Proposed vs ResNet	103,598	00.00	There is a significant difference
ShuffleNet Proposed vs ShuffleNet	56,3295	00.00	There is a significant difference

Table 5 shows very high T-statistic values and very low p-values (all < 0.05), which indicates that the difference between Proposed ShuffleNet and other models is statistically significant.

In addition to the T-test, the Wilcoxon signed-rank test was also conducted to examine differences in model performance that are more sensitive to non-normal data distributions [51], [52]. The detailed results of the Wilcoxon test for all model pairs are presented in Table 6.

Table 6. Wilcoxon Test Results

Model Comparison	Z-statistic	p-value	Result
ShuffleNet Proposed vs MobileNet	7.693	00.00	There are significant differences between ShuffleNet Proposed and MobileNet.
ShuffleNet Proposed vs ResNet	8.544	00.00	There are significant differences between Proposed ShuffleNet and ResNet.
ShuffleNet Proposed vs ShuffleNet	7.247	00.00	There are significant differences between ShuffleNet Proposed and ShuffleNet.

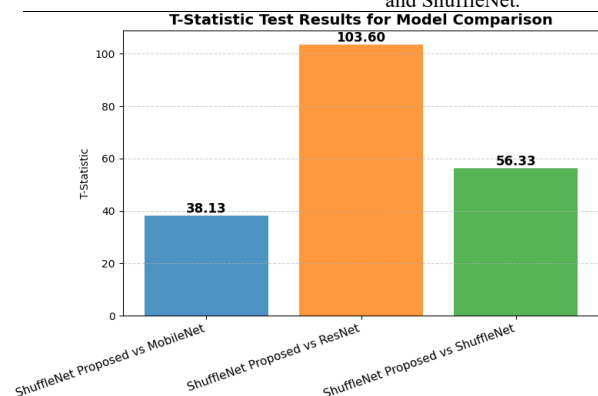


Figure 11. Comparison Graph of T-Test Results

As can be seen in Table 6, the results of the Wilcoxon test show that all pairs of models also show significant differences with very small p-values (all < 0.05). The

overall comparison of the statistical test results is illustrated in Figure 11.

Based on the results of the T and Wilcoxon tests, it can be concluded that ShuffleNet Proposed shows significantly better performance than other models, such as MobileNet, ResNet, and ShuffleNet. This statistical test shows that the differences in accuracy found are not caused by chance factors or dataset characteristics, but rather differences in model architecture.

4. Conclusions

This study shows that the ShuffleNet Proposed algorithm (a modification of ShuffleNet) outperforms other models due to its very high accuracy (99%) without experiencing overfitting, so that the model can generalize well to new data. The very high F1-Score, precision, and recall (99%) indicate the model's balanced ability to detect classes while minimizing errors. The techniques applied to ShuffleNet Proposed, such as dropout, early stopping, and learning rate scheduler, improve model stability and prevent overfitting. Although ShuffleNet achieves 100% results, this model is at risk of overfitting, while ShuffleNet Proposed provides more realistic results while maintaining very high performance. The results of statistical tests (T-test and Wilcoxon) show that the difference in accuracy between ShuffleNet Proposed and other models, such as MobileNet, ResNet, and ShuffleNet, is significant, which strengthens the claim that the difference in performance is not a coincidence or dataset characteristic, but rather due to differences in model architecture.

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