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Rice quality classification system using convolutional neural network and an adaptive neuro-fuzzy inference system

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ABSTRACT

In the food sector, rice processing and classification are essential operations that help maintain strict quality and safety standards, satisfy various consumer preferences, and satisfy particular market demands. Artificial intelligence (AI) and machine learning techniques are used in automated systems to reliably and effectively classify rice quality. This research compares a rice quality classification system using a convolutional neural network (CNN) and an adaptive neuro-fuzzy inference system (ANFIS). Both methods are evaluated for their ability to classify rice based on quality, utilizing a dataset encompassing various physical characteristics. The comparative analysis results reveal the strengths and weaknesses of each approach in addressing this classification task. In this research, two classification systems for different varieties of rice-medium and premium—are compared. CNN and ANFIS are the techniques applied. The CNN accuracy on the rice picture is 62.5%. Thus, a contrast enhancement procedure was applied and had better accuracy at 75%. However, when contrasted with the classification made using the ANFIS approach, the ANFIS method continued to yield the best accuracy, 82.25%.

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1. INTRODUCTION

Rice is a staple food commodity central to fulfilling human dietary needs worldwide. The quality of rice is paramount in determining its commercial value and use in various food products such as rice, rice flour, and processed foods. Quality differences in rice encompass parameters such as colour, size, texture, and aroma. Manual classification of rice quality is a time-consuming and subjective task that can result in errors [1]. Proper classification facilitates compliance with international regulations for export and import, supporting global trade of this essential commodity. Additionally, the economic impact is significant, as the quality assurance achieved through processing and classification enhances the market value of rice products, benefiting both producers and the broader economy [2], [3].

Automated methods for efficiently and accurately classifying rice quality utilize advanced technology and machine learning techniques. One common approach is to employ computer vision and image analysis to assess various rice attributes, including colour, size, and shape [4]. The current process of rice classification typically involves a combination of traditional and modern methods, depending on the level of automation and technology used in the rice processing industry. The human inspection process involves operators who visually inspect and classify rice grains. This assessment is often subjective and can lead to variations in classification results. Some rice processing facilities use mechanical equipment that automatically sorts rice based on specific physical parameters, such as size and weight. However, they may be unable to classify based on more complex criteria like colour or texture [5]. Rice samples can be sent to laboratories with chemical and physical analysis equipment for more in-depth quality testing [6]. These tests include monitoring moisture content, starch content, and other factors that affect rice quality. Many rice processing facilities currently use laboratory methods, such as human inspection for visual assessment and sorting machines for size-based sorting [7], [8].

Convolutional neural network (CNN) is a highly effective artificial neural network (ANN) architecture in image processing and pattern recognition tasks. It was primarily developed to handle visual data such as images and videos and has become a core technology in computer vision and image processing [9]. CNN have several advantages, including the ability to understand hierarchical features in images, invariance to transformations, utilization of correlated data, automatic feature extraction, scalability for various tasks, the use of pre-trained architectures, the ability to handle large-sized data, improved accuracy in image recognition, and utilization of hardware acceleration [10]. Koklu *et al.* [2] uses ANN and CNN algorithms to classify and evaluate the quality of seeds from five different rice varieties in Turkey. The ANN and deep neural network (DNN) algorithms were used for the feature dataset, while CNN was used for the image dataset. The classification success rates were 99.87% for ANN, 99.95% for DNN, and 100% for CNN, demonstrating the successful application of these models in rice variety classification.

In recent years, research has focused on image processing technology and intelligent systems like the adaptive neuro-fuzzy inference system (ANFIS) [11], [12]. Applying ANFIS in rice colour analysis offers the potential to classify rice with high precision based on measurable colour characteristics. ANFIS is a computational model that combines elements from ANN and fuzzy inference systems to address problems involving uncertainty and ambiguous data [13]. It utilizes fuzzy membership functions to measure the degree of membership of elements in one or more fuzzy sets, employs fuzzy rules to express relationships between inputs and outputs, performs a fuzzy inference process to compute membership values, incorporates a neural network model with learned weights to adapt to data, and matches the fuzzy inference results with the neural network output to generate an outcome [14]. ANFIS is known for its ability to handle ambiguous data, rule-based interpretability, and flexibility in decision-making based on fuzzy concepts, finding applications in industrial process control, recommendation systems, pattern recognition, and prediction tasks [12].

Research on rice quality classification has been carried out using various methods such as the CNN method, multi-class support vector machines (SVM), back propagation neural network (BPNN), and ANFIS [15]. Mandal [16] proves that ANFIS can classify rice into whole rice grains, broken rice grains, and imperfect rice grains with 98.5% accuracy. However, the data set in this study was taken with images of individual rice, even though, in reality, humans observe the quality of rice as a collection of rice, not one by one. So, this research takes the image of rice as a collection. Research by Zia *et al.* [17], the visual geometry group (VGG-19) machine-learning technique was used to evaluate damaged and undamaged rice seeds and rice models with brown spots, with an accuracy of 98.8% and 100%, respectively. This research also produces a website-based application that can classify types of damaged and undamaged rice based on 1 grain of rice, not based on a collection of grains. This is the difference between the proposed research and the proposed research because the proposed research classifies the quality of rice at medium and premium levels based on the image of the rice collection.

In this research, a system was created to assess the quality of rice based on its colour using the ANFIS method. This research will explain 3 (three) models that represent machine learning used to assess rice quality based on colour. The three models are the CNN model using an image generator, the CNN model using a combination of image generator and cv2, and the ANFIS model implemented in Python [18]. The three models will be seen to compare their performance accuracy. From this comparison, it can be concluded which model best assesses rice quality based on colour.

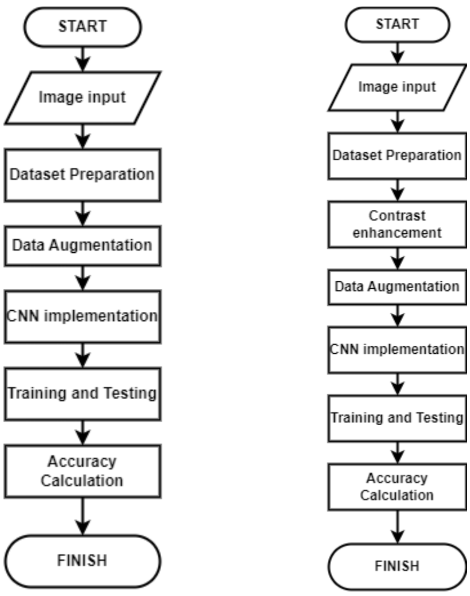
2. METHOD

2.1. Classification using convolutional neural network

Designing CNN MobileNetV2 is the first step in designing an application. The focus of the discussion is only given to evaluating the accuracy produced by the CNN model. There are 2 (two) variations of the MobileNetV2 CNN model will be used as a comparison in this research. The first variation is a CNN model using an image generator, and the second is a CNN model that combines an image generator with the cv2 library [19], [20]. The design of the CNN model has several purposes, including visual data processing, such as pattern recognition, object detection, classification, segmentation, and other tasks. Classifying rice into two categories, medium and premium, using CNN involves structured steps, starting with data collection and pre-processing. In the initial phase, a diverse dataset of rice images is gathered, ensuring that each image is appropriately labelled with its corresponding class. These images undergo pre-processing, resized to a consistent dimension, normalized pixel values, and data augmentation techniques are applied to enhance the dataset's variability.

The next step is the design of the CNN architecture. It involves stacking convolutional layers to extract features, pooling layers for spatial down-sampling, and fully connected layers for decision-making. The architecture is then trained on the labelled dataset using a chosen loss function, such as categorical cross-entropy, and optimized through backpropagation. Transfer learning, starting with a pre-trained model and fine-tuning it for rice classification, is often employed to leverage knowledge from models trained on large datasets like ImageNet. Hyperparameter tuning follows, where parameters like learning rate, batch size, and dropout rates are adjusted to optimize the model's performance [21]. The trained model is then evaluated on a validation set to ensure it generalizes well to unseen data and subsequently tested on a separate test set for real-world assessment. Post-training, the model's output probabilities are analyzed, and a decision threshold is set to classify rice images into medium or premium. Post-processing steps include refining the decision boundaries based on specific criteria. The model's performance is thoroughly evaluated using metrics like accuracy, precision, recall, and F1 score, focusing on understanding and addressing misclassifications [22], [23].

The purpose of the CNN model using an image generator is to overcome the problem of limited or unbalanced data in a certain number of classes or categories in the dataset. An image generator is a tool that allows dynamically generating new image variations from the original image with various transformations such as rotation, shift and crop. The design of this model starts from input images and ends with accuracy calculation, as shown in Figures 1(a) and (b).



(a) (b)

Figure 1. Classification using (a) CNN and (b) CNN with contrast enhancement

The image input stage begins by collecting a dataset of rice images used in the rice quality classification process. The collection of rice quality image datasets was carried out through two methods: by shooting rice according to its quality, namely medium rice and premium rice. After that, the dataset will be divided into two parts: the training and testing sets. Then, the process of restructuring the dataset will be carried out. This stage is essential in pre-processing data before starting model training or data analysis. The goal is to keep datasets structured, easily accessible, and ready to use in various data analyses.

Data augmentation is commonly used in training ANN models, such as CNN, to improve model performance and generalization. Data augmentation involves image transformations, such as rotation, shifting, zooming, or cropping, as well as applying effects such as horizontal flips or colour changes. The process of implementing this CNN model uses the TensorFlow library. This CNN model uses MobileNetV2 as an architecture using training (pre-trained) on the ImageNet dataset [24]. The convolution layer performs convolution operations using filters or kernels, where each kernel identifies specific patterns or features in the image. MobileNetv2 also organizes these layers in "blocks", which are collections of CNN layers grouped for specific tasks. Each block can have different CNN layers to extract image features with different levels of complexity. The training process is carried out to teach the model, and the training results are visualized [25]. The model is then evaluated using prepared training data and test data. The data obtained in this model is data without going through an image enhancement (contrast enhancement) process. In the CNN design integrated with contrast enhancement, there is an increase in the pre-processing stage, where the image contrast is increased before the dataset is augmented. OpenCV plays a role in increasing image contrast, and the results of increasing the contrast are then used in the dataset augmentation process using the image generator.

2.2. Classification using adaptive neuro-fuzzy inference system

ANFIS combines ANN working principles with fuzzy inference systems (FIS). It allows ANFIS to achieve a higher level of intelligence in decision-making and inference from uncertain and complex data. The design of the ANFIS model is shown in Figure 2. In preparing this dataset, changes to data and labels will be made in NumPy arrays. Data and labels must be converted into NumPy arrays to be processed efficiently by various libraries and data processing tools commonly used in Python programming, especially in training machine learning or deep learning models such as CNN [26]. In this process, the dataset is divided into two parts, namely 80% for training data and 20% for testing data.

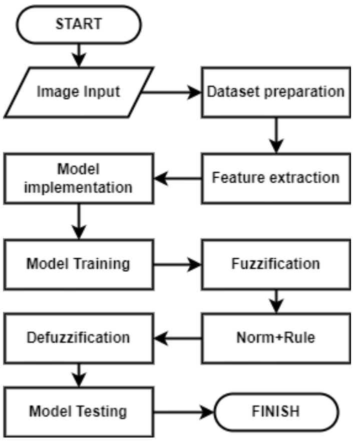


Figure 2. Classification using ANFIS

This process begins with the feature extraction stage of each image in the dataset. Feature extraction is essential in image processing before the data can be used in machine learning or deep learning model training, especially in pattern recognition or classification. In this model, the feature extraction method used is RGB feature extraction, which is a simple approach to extract statistical information from the primary colour components, namely red (R), green (G), and blue (B) in an image. A neural network model will be combined with fuzzy logic at this stage. ANN is used for tasks such as classification and regression. Fuzzification is a fuzzy inference system step that converts the model output (ANN) into linguistic or fuzzy variables [19], [20]. In this process, we used the Gauss function as the membership function of an element in the fuzzy set. In the Norm+rule stage, a comparison is made, and the maximum membership level is determined between the model predictions ("medium" or "premium") and the previously created membership function. It will be used in defuzzification's next step to produce a more concrete output. The defuzzification stage is where the previously calculated fuzzy membership levels are converted into a single or concrete value representing the final result of the fuzzy inference system. In this context, the defuzzification method used is the centroid. A centroid is a single value generated from the defuzzification process in a fuzzy inference system. This value represents the midpoint or centre of the calculated fuzzy membership distribution.

3. RESULTS AND DISCUSSION

Contrast enhancement is used in CNN pre-processing to increase the sharpness and clarity of features in the image. It can help the CNN model better to identify relevant patterns and features in the image. Contrast enhancement can be a crucial pre-processing step if the images initially have low contrast or if it is necessary to highlight important details in the image. This model's dataset consists of rice images, generally bright white or off-white. However, sometimes, the colour difference between the two types of rice may be hard to see because they share a high degree of resemblance. Therefore, in the pre-processing process, contrast enhancement is applied to the image to clarify colour differences and features that may be difficult to recognize in low-contrast images. The differences between the rice classes are shown in Figure 3.

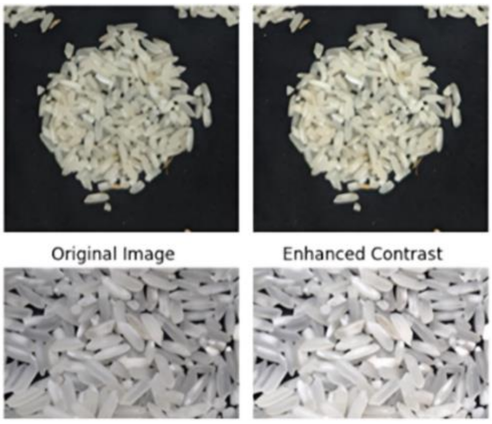


Figure 3. The results of contrast enhancement

The total data of 308 rice images will be divided into 2 data: training data from 246 rice images and test data from 62 rice images. This study divides the test into three parts: testing the CNN Mobilenetv2 model using an image generator, the CNN Mobilenetv2 model using a combination of image generator and cv2, and the ANFIS model. By conducting this test, this study can identify the effectiveness and accuracy of each model. The output of the CNN model is as follows:
Accuracy on training data: 0.6641
Loss of training data: 4.2733
Accuracy on test data: 0.7500
Loss on test data: 3.3561
- 4s 779 ms/stop – loss: 4.8639 - Accuracy: 0.6250
Accuracy: 62.5 %

The results of this evaluation provide an understanding of the extent to which the CNN model can understand and classify image data accurately. From the program output results, it can be concluded that the model achieved an accuracy level of around 66.41% on the training data. This accuracy reflects how well the model can identify and classify data in the training data. Apart from that, the training data has a loss value of 4.2733. This loss value describes the extent of the difference between the model predictions and the actual values in the training data. The lower the loss value, the better the model adapts to the training data. The model achieves an accuracy rate of around 75.00% on test data. This accuracy indicates how well the model can predict data that has never been seen before.

Furthermore, there is a loss value of 3.3561 in the test data. The loss value on test data measures how well the model can generalize to new data not included in the training data. The output from measuring model accuracy using the test data set obtained an accuracy of 62.5%. Testing the CNN Mobilenetv2 model using a combination of image generator and cv2 library is to evaluate the model's ability to classify rice quality. The output of the CNN model with contrast enhancement is as follows:
Accuracy on training data: 0.7422
Loss on training data: 3.0692
Accuracy on test data: 0.7500
Loss on test data: 3.4488
- 3s 3s/step - loss: 2.9940 - Accuracy: 0.7500
Accuracy: 75.0 %

The results of this model evaluation show that the model achieves an accuracy rate of 74.22% on the training data, indicating how well the model can understand the patterns contained in the training data. The higher the accuracy of the training data, the better the model's ability to adapt to the data used for training. This CNN model has a loss rate of about 3.0692 in the training data, which reflects the degree to which the model successfully matches the training data. The lower the loss value, the better the model matches the data. Meanwhile, the model achieves an accuracy rate of around 75.00% on the test data.

In testing the ANFIS model, four testing stages play an essential role in evaluating model performance: first, testing the accuracy of the neural network model as an assessment of whether the combined model is feasible—second, class prediction testing to assess the success of the ANFIS model in predicting rice quality. Third, testing uses a confusion matrix as a more detailed evaluation tool for the running model. Finally, testing with the classification report provides more detailed information about the performance of the classification model beyond just looking at the confusion matrix or just the level of accuracy.

The ANN model managed to achieve an accuracy rate of 82.25%. This accuracy follows the targets previously determined in selecting the neural network model that will be combined with fuzzy logic. By achieving this level of accuracy, the ANN model can be well used in combination with fuzzy logic to continue building the ANFIS model. Testing the confusion matrix in the ANFIS model is needed to measure the extent to which the model can correctly perform classification. The results of the confusion matrix of the ANFIS model are shown in Table 1.

Table 1. Confusion matrix

		Predicted Label	
		Medium	Premium
Actual label	Medium	35	4
	Premium	7	16

Table 1 shows the results of the confusion matrix of the ANFIS model, which states that there are 35 medium predictions, which are medium (true positives), 4 premium predictions which should be medium (false negatives), 7 medium predictions which should be premium (false positives), and 16 predictions an indeed premium (true negatives). The purpose of testing the classification report of the ANFIS model is to provide more detailed and detailed information about the performance of the classification model in the context of testing. Classification reports provide several evaluation metrics, including precision, recall, F1-score, and support, as shown in Table 2. The graph of the difference in accuracy between the CNN method, CNN with contrast enhancement and ANFIS is shown in Figure 4. The results show that the ANFIS method has the highest accuracy.

Table 2. Classification report

	Precision	Recall	F1-Score	Support
Medium	0.83	0.90	0.86	39
Premium	0.80	0.70	0.74	23
Accuracy			0.82	62
Macro avg	0.82	0.80	0.80	62
Weighted avg	0.82	0.82	0.82	62

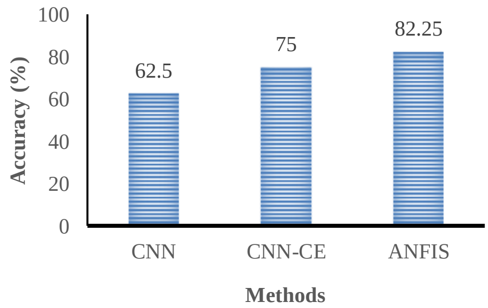


Figure 4. Overall accuracy

The accuracy of the classification results in this study reached 62.5%, which is relatively low compared to Hamzah and Mohamed [5], which was more than 90%. It is because, based on several references that discuss the CNN method, it is suitable for large datasets. Machine learning techniques, such as SVM, are used to classify rice grains accurately [21]. A rice grain image study underwent pre-processing, segmentation, and feature extraction. The multi-class SVM was used to classify three types of rice grains: basmathi, ponni, and brown rice. The study achieved 92.22% classification accuracy, better than the accuracy of the proposed methods using ANFIS. It is because the proposed research takes images in collection form and is classified not based on shape but on colour and texture, as rice buyers do in reality. Of course, this will result in a classification process that is quite difficult because it is adapted to observations using the human eye. ANFIS and CNN are distinct machine learning approaches, each with its strengths and areas of applicability. It is not accurate to definitively claim that one is superior to the other, as their performance depends on the nature of the task at hand. ANFIS creates interpretable rule-based models, making it valuable in domains requiring decision-making transparency, like expert systems and medical diagnosis. Additionally, ANFIS excels in handling data with ambiguity or uncertainty, where the relationships between inputs and outputs are not well-defined. When the system has limited labelled data, it can often provide reasonable predictions with smaller datasets.

4. CONCLUSION

This research compares two methods to classify types of rice into two classes, namely medium and premium. The methods used are CNN and ANFIS. Because the CNN accuracy is not very good, a contrast enhancement process is carried out on the rice image. There was an increase from 62.5% to 75%. However, when compared with the classification using the ANFIS method, the highest accuracy was still obtained through the ANFIS method, which was 82.25%. CNN and ANFIS are valuable machine learning approaches, each with strengths and areas of applicability. ANFIS excels in creating interpretable rule-based models, handling ambiguous or uncertain data, and providing reasonable predictions with smaller datasets. It can be applied to various data types, such as time series, tabular data, and text, and is computationally simpler than deep CNNs. CNNs are preferred for image-related tasks and deep learning, outperforming ANFIS in computer vision applications.

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