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A Rice Quality Classification Model Using Machine Learning Technique

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Abstract

This study proposes a rice quality classification method using Convolutional Neural Network (CNN) to improve the accuracy and efficiency in classifying rice into premium, medium, and low. This study involves processing digital images of rice with data augmentation techniques, feature extraction using convolution layers, and classification using CNN models. The dataset used consists of rice images obtained through direct photography and open sources. This data is then divided into training, validation, and test data to improve model performance. Model training was carried out using Google Colab with Adam optimization and ReLU activation function. The test results showed that the CNN model was able to classify with an accuracy level of 85%, higher than conventional methods. Rice grain image data was collected and processed through preprocessing stages such as normalization and segmentation, then feature extraction was carried out. The rice image feature extraction values obtained include: Red 164.7719; Green 68.3355; Blue 61.7290; Hue 0.4037; Saturation 0.6625; Value 0.6462; and Area 493023 pixels.

Keywords: *Classification; Rice; Digital Image; Convolutional Neural Network (CNN)*

1. Introduction

Rice is a strategic commodity that is highly essential to society. As a staple food, rice plays a vital role in meeting daily needs, making it one of the leading products in the national food and agricultural sectors. Rice production in Indonesia is highly diverse, both in terms of types and quality. Consumers often seek high-quality rice such as super, premium, or medium grades, as rice is classified based on its quality level and type. Currently, many producers sell various types of rice without considering market preferences, which risks losses due to unsold products accumulating in warehouses. Therefore, managing rice sales requires serious attention, as rice quality greatly influences consumer purchasing decisions. Consumers tend to assess rice quality based on packaging and characteristics such as soft texture, stickiness, and whole grain shape. If the rice quality meets consumer expectations, the likelihood of the product being favored in the market increases significantly [1].

Rice quality is a crucial factor in the agricultural industry as it directly affects market value and consumer satisfaction. High-quality rice not only has an attractive physical appearance but also meets specific standards in terms of taste, texture, and nutritional content. Accurate rice quality assessment is essential to ensure that the produced products meet market expectations and international standards [2].

Rice quality is influenced by several physical characteristics, including (1) grain size and shape, (2) milling degree, (3) clarity, and (4) cleanliness and purity. Since rice is consumed in whole grain form, these physical attributes play an important role in its quality. Rice can be categorized based on its shape and color. The whiter, cleaner, and more intact the rice, the better its quality. The degree of whiteness and cleanliness can be assessed through HSV value analysis of rice images, while the level of grain integrity is determined through object area analysis. Based on its quality, rice can be classified into premium, medium, and unfit categories [3].

To determine which rice quality is most preferred by consumers, several classification methods can be used, including the Naïve Bayes Classifier (NBC) and K-Nearest Neighbor (K-NN). The Naïve Bayes Classifier is a statistical application based on class probability predictions. Meanwhile, the K-Nearest Neighbor (K-NN) algorithm is a lazy learning method that spends more time during the classification phase, where no model is learned from the test data, and the goal is to classify objects based on attributes and training data [4].

The advancement of information technology and machine learning algorithms offers solutions to address this issue. Machine learning allows for efficient and accurate processing of large and complex datasets. The Convolutional Neural Network (CNN) method, one of the simplest yet effective algorithms, works by classifying new data based on its similarity to known data. In this study, we will utilize the physical features of rice to train a CNN model and evaluate its performance in classifying rice quality. The results of this study are expected to make a tangible contribution to improving the efficiency and accuracy of rice quality assessment processes in the agricultural industry and pave the way for the application of machine learning techniques in other related fields [5].

A study by Febriyanti Paramudita and Mulki Indana Zulfa (2023), titled "Android Application for Rice Quality Detection Based on Machine Learning Using Convolutional Neural Network Method", discusses rice quality as a staple food and a primary ingredient in various food products, which requires a certain quality level. Rice quality includes physical properties that affect its appearance and determine its quality when cooked. This necessitates the need for an efficient method of detecting rice quality. The study presents an Android application for rice quality detection based on machine learning. The application development method used was Agile, offering flexibility in handling changing requirements and user feedback during the development process. Furthermore, the machine learning model was built using the Convolutional Neural Network (CNN) method with the TensorFlow and Keras libraries and the MobileNet architecture. The programming language used was Python, with the simulation environment in Google Colab. The developed model was trained using a dataset of 1800 images, 1440 of which were used for training with 25 epochs. The simulation results showed a training loss of 0.0012 and an accuracy of 99.44% [6].

Another study conducted by Tiara Virlianda Herliana et al., titled "Classification of Delanggu Rice Quality Based on Texture Features Using Gray Level Co-Occurrence Matrix and Naïve Bayes", discusses the quality of rice, which is a staple food for the Indonesian population. One of the largest rice-producing regions in Indonesia is Delanggu, located in Klaten Regency, Central Java. Various types of rice available in the market have different qualities in terms of color, texture, and aroma. As rice plays a vital role in the Indonesian diet, public demand for rice consumption remains high. However, the annual fluctuation in staple food prices has led to a decrease in purchasing power and, in some cases, fraudulent practices such as mixing rice of different qualities. Therefore, a technology that can help both the public and the government to identify rice quality in the market is necessary to determine its suitability. This study developed a machine learning-based system to identify rice quality using images. For classification, the authors used the Naïve Bayes method, while for feature extraction, they employed the Gray Level Co-Occurrence Matrix (GLCM) method to determine rice texture. Based on the tests conducted, the system was able to identify Delanggu rice based on two quality categories: super and regular. The testing was performed using 40 rice images, with each class containing two quality categories. The best second-order parameter testing scenario in the combination of two second-order GLCM features produced the highest accuracy, namely contrast-correlation with 100.00% accuracy and a computation time of 82.59 seconds, using an angle of 135° and a pixel distance of d=1 [7].

2. Research Methodology

In carrying out this research, the activities conducted include studying the development of the model and methods to be used. The model development method employed in this research follows a sequence consisting of conducting a literature review, finding a dataset, processing the dataset, designing the model, testing the model, and collecting the results of the research. The following is the flow of the research model:

a. Literature Review, the author conducts the collection of theories related to the research topic. This is done through a literature review. In this stage, the author refers to several readings related to the Rice Quality Classification Model using Machine Learning techniques with the CNN method. The references used may include theories or opinions taken from books or relevant journals. This aims to provide a strong theoretical foundation through the literature used by the author [8].

b. Dataset Collection, collecting a dataset for research on rice quality classification using the CNN method is a crucial step to ensure that the developed model has sufficient and representative data. This process begins with defining the research objective and dataset requirements, namely classifying rice quality based on features extracted from rice images.

c. Training / Testing, the processed dataset is divided into two parts: training data and testing data. The training data is used to train the model, while the testing data is used to evaluate the model's performance. A common split is 80% for training and 20% for testing. Cross-validation can also be applied to ensure the model does not over fit.

d. Model Design, Designing the rice quality classification model using the CNN method involves several important systematic steps. The first step in model design is collecting data, which includes rice images from various varieties and quality levels. The data must be representative to ensure that the model can recognize the variations in rice samples. Once the data is collected, preprocessing is carried out, including cleaning, normalization, and standardization, to ensure the data is in a consistent format and ready for training.

e. Model Testing, at this stage, several tests are performed on the implemented model. The testing is done through systematic trials of the rice quality classification model using the CNN method. The testing approach used in this research is Black Box Testing, which aims to determine whether the software functions and operates as expected.

f. Data Result Collection, collecting data results in the research on rice quality classification using the CNN method is a crucial stage to evaluate the performance of the developed model. This process begins by applying the trained and optimized CNN model to the testing data that the model has not seen before. This testing data must reflect the variation and characteristics of real-world data to ensure the model can generalize well beyond the training data.

2.1. Introduction to Rice Image Recognition

Rice is the part of the rice grain that has been separated from the husk. The husk (called merang in Javanese) is anatomically referred to as the palea (the covered part) and the lemma (the covering part). Like other cereal grains, rice is mostly composed of starch (about 80–85%). It also contains protein, vitamins (especially in the aleuronic layer), minerals, and water. However, rice varies in quality; therefore, monitoring the quality of rice distributed in the market is crucial as it affects both sales and consumption levels [9].

Rice quality varies based on specific characteristics. Whole grains, head rice, broken grains, and brewers are the primary parameters of rice quality as defined in the Indonesian National Standard (SNI), as shown in Figure 1 below.

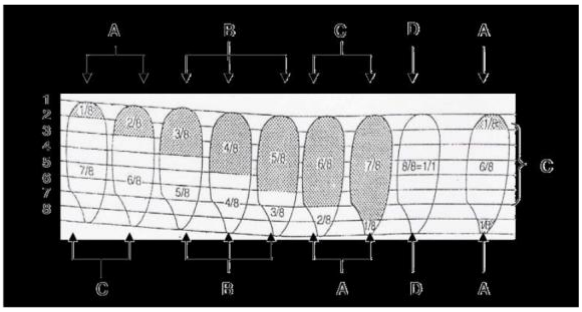


Fig. 1: Parts of Rice Grains: (A) Small Broken (B) Large Broken (C) Head Rice (D) Whole Rice Grain

2.2. Machine Learning

Machine Learning, a branch of artificial intelligence, is a scientific discipline that involves the design and development of algorithms that enable computers to develop behaviour based on empirical data, such as data from sensors or databases. Learning systems can utilize examples (data) to capture essential characteristics of the underlying (and unknown) probability distribution.

Data can be viewed as examples that describe relationships between observed variables. A major focus of machine learning research is how to automatically recognize complex patterns and make intelligent decisions based on data. The challenge lies in the fact that the set of all possible behaviours, from all possible inputs, is too large to be covered by the set of observed examples (training data). Therefore, learning must generalize behaviour from the available examples to produce useful outputs in new or unseen cases [10].

2.3. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a type of artificial neural network specifically designed to handle image data. CNNs are widely used in various applications such as image classification, object detection, and image segmentation due to their ability to extract important features from images. This algorithm works by mimicking the way the human visual cortex recognizes patterns and structures in images. CNN consists of several main layers—namely, the convolutional layer, pooling layer, and fully connected layer—which work sequentially to process and analyse visual data [2].

The convolutional layer is the core component of CNN, responsible for extracting features from images. In this layer, filters (also called kernels) move across the image to detect specific patterns such as edges, corners, or textures. This process produces a feature map, which is a numerical representation of the features in the image. Each convolutional layer contains multiple filters with different sizes, allowing the network to capture various levels of detail. Activation functions such as ReLU (Rectified Linear Unit) are often used to introduce non-linearity and help the model learn more complex patterns.

After passing through the convolutional layers, CNNs use pooling layers to reduce the dimensions of the feature maps while preserving the most important information. This layer aims to improve computational efficiency and make the model more robust to small changes in the input image (translation invariance). Common types of pooling include max pooling, which selects the maximum value within a small region of the feature map, and average pooling, which computes the average value within that region. With pooling layers, CNNs can reduce the number of parameters to process without losing essential information [3].

After several convolutional and pooling layers, CNNs utilize fully connected layers (FCLs) to connect the extracted features with the classification process. This layer operates similarly to a traditional artificial neural network (Multilayer Perceptron - MLP), where each neuron in one layer is connected to every neuron in the next layer. At the final stage, a softmax activation function is typically used to convert the output into probabilities for each possible class, allowing the model to determine the most likely category of the analysed image [11].

2.4. Application of the CNN Method

Another strategy applied is the adjustment of the CNN architecture and the optimization of hyper parameters. By using the right combination of convolutional and pooling layers, the model can extract features more efficiently without losing important information. The use of activation functions such as ReLU helps enhance the model's non-linearity, while softmax or sigmoid activation functions in the output layer ensure effective classification. Additionally, techniques such as dropout can be employed to prevent overfitting. From the optimization perspective, the Adam algorithm with an appropriately tuned learning rate can accelerate the training process and improve accuracy. With this combination of strategies, the CNN model is expected to achieve accurate classification and be implemented in an automated rice quality assessment system. In the rice quality classification system, the data used consists of rice image data collected from premium-quality, medium-quality, and low-quality rice.

The stages in determining rice quality using the Convolutional Neural Network (CNN) algorithm begin with inputting rice images, where the rice images are captured and entered into the system. The images then go through a pre-processing stage, including resizing, colour normalization, and data augmentation, if necessary. This step aims to improve data quality so that the CNN model can more easily recognize patterns in the images. Next, the pre-processed data is split into training data and validation data, which are used to train the CNN model.

The model is then trained using several convolutional and pooling layers to extract important features from the rice images. Once the CNN model has been trained, the system proceeds to the model evaluation stage, where its accuracy and performance are measured using test data. If the model achieves sufficiently high accuracy, it is then used to predict rice quality by comparing feature patterns in the image against the learned data. Based on the prediction results, the system determines whether the rice falls into the premium, medium, or low quality category. Finally, the classification results are presented to the user in the form of an output that shows the rice quality based on the trained model.

Below is an example of a calculation using the Convolutional Neural Network (CNN) method with feature extraction data obtained, as shown in the table below.

Table 1: The Rice Image Dataset

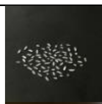
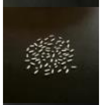
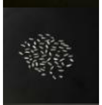
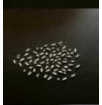
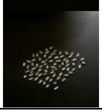
No.	Image	Description
1		Premium
2		Premium
3		Medium
4		Medium
5		Premium
6		Premium
7		Low
8		Premium
9		Low
10		Medium
11		?

Table 2: Dataset for Feature Extraction of Rice Images

No	Red	Green	Blue	Hue	Saturation	Value	Area	Description
Citra 1	93,7616	111,2652	46,4703	0,2098	0,6431	0,4366	395138	Premium
Citra 2	86,9260	94,9331	36,2775	0,1877	0,6947	0,3742	665020	Premium
Citra 3	93,0500	94,5617	55,4094	0,1775	0,4681	0,3895	997294	Medium
Citra 4	85,0228	84,4169	52,9123	0,1677	0,3986	0,3515	506041	Medium
Citra 5	77,5005	102,2545	42,8314	0,2649	0,6197	0,4049	378860	Premium
Citra 6	95,9700	82,9862	54,5784	0,1178	0,4587	0,3787	616553	Premium
Citra 7	94,6524	108,3329	37,7670	0,1860	0,6521	0,4303	336008	Premium
Citra 8	91,6542	108,3320	37,7681	0,1862	0,6524	0,4302	336001	Premium
Citra 9	86,1705	104,0520	28,2179	0,2043	0,8319	0,4087	348356	Premium
Citra 10	122,5048	128,9050	68,0122	0,1762	0,5281	0,5079	308022	Medium
Citra 11	164,7719	68,3355	61,7290	0,4037	0,6625	0,6462	493023	?

Table 3: Data Testing

No	Red	Green	Blue	Hue	Saturation	Value	Area	Description
Citra 16	164,7719	68,3355	61,7290	0,4037	0,6625	0,6462	493023	?

The extracted feature values from the rice image include: Red 164.7719; Green 68.3355; Blue 61.7290; Hue 0.4037; Saturation 0.6625; Value 0.6462; and an Area of 493,023 pixels, with a classification of medium quality.

3. Results and Discussion

Rice image data testing was conducted using Python on Google Colab. Google Colab is highly suitable for data processing and machine learning as it supports Python, TensorFlow, OpenCV, and other libraries useful for rice image classification. The following are the steps carried out for testing the rice images.

3.1. Data Loading

The process involves connecting Google Colab to Google Drive so that the dataset stored in Drive can be accessed and used in the rice quality classification model. This step is important because datasets are often large and cannot be stored directly in Google Colab's local storage, thus requiring integration with Google Drive as an external storage location.

3.2. Data Pre-processing

The "Data Pre-processing" stage, specifically the "Dataset Preparation and Splitting" step, is a critical part of developing a rice quality classification model using CNN. This stage includes Dataset Management, Dataset Splitting, and Data Distribution.

3.3. Data Splitting and Dataset Verification

Data Splitting and Dataset Verification are part of the Data Pre-processing stage in the development of a machine learning model. In this stage, the rice image dataset is divided into two main groups: a training set and a validation set, based on a predefined ratio (90% for training and 10% for validation). After the splitting is performed, the code prints the number of data samples in each category (Premium, Medium, and Low) to ensure that the division was executed correctly. However, based on the displayed results, there is an inconsistency in the total number of data samples before and after the split, which may indicate an error in file transfer. Therefore, this stage also serves as dataset verification, ensuring that the data is available in the correct quantities before being used in the CNN-based classification model training process.

3.4. Convolutional Neural Network Method

The model is built with several layers, including Conv2D for feature extraction, MaxPooling2D for reducing feature dimensions, Flatten to convert the data into a one-dimensional vector, and Dense and Dropout layers to improve classification performance. The model is compiled using categorical_crossentropy as the loss function and Adam as the optimizer with a learning rate of 0.1. Next, the model is trained using a preprocessed dataset with ImageDataGenerator, where the training process runs for 20 epochs with callbacks to stop the training early if accuracy reaches a certain threshold. The model is then evaluated using validation data (val_generator) to measure its accuracy and performance in classifying rice images into three categories. The training data process is illustrated in the image below.

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 148, 148, 16)	448
max_pooling2d_6 (MaxPooling2D)	(None, 74, 74, 16)	0
conv2d_7 (Conv2D)	(None, 72, 72, 32)	4,640
max_pooling2d_7 (MaxPooling2D)	(None, 36, 36, 32)	0
conv2d_8 (Conv2D)	(None, 34, 34, 64)	18,496
max_pooling2d_8 (MaxPooling2D)	(None, 17, 17, 64)	0
flatten_2 (Flatten)	(None, 18496)	0
dense_6 (Dense)	(None, 200)	3,699,400
dropout_4 (Dropout)	(None, 200)	0
dense_7 (Dense)	(None, 500)	100,500
dropout_5 (Dropout)	(None, 500)	0
dense_8 (Dense)	(None, 3)	1,503

Total params: 3,824,987 (14.59 MB)
Trainable params: 3,824,987 (14.59 MB)
Non-trainable params: 0 (0.00 B)

Fig. 2: Data Training

```
Epoch 1/20
6/9 ━━━━━━━━━━━━━━━━━━━━ 2s 750ms/step - accuracy: 0.2119 - loss: 101651.1484/usr/local/lib/python3.11/dist-packages/ke
  self._interrupted_warning()
9/9 ━━━━━━━━━━━━━━━━━━━━ 8s 583ms/step - accuracy: 0.2080 - loss: 91516.7422 - val_accuracy: 0.3333 - val_loss: 2.7121
Epoch 2/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 6s 582ms/step - accuracy: 0.2669 - loss: 2.6563 - val_accuracy: 0.3333 - val_loss: 1.5832
Epoch 3/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 9s 423ms/step - accuracy: 0.3239 - loss: 1.6604 - val_accuracy: 0.3333 - val_loss: 1.1711
Epoch 4/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 6s 586ms/step - accuracy: 0.5015 - loss: 1.1789 - val_accuracy: 0.3333 - val_loss: 1.2721
Epoch 5/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 4s 420ms/step - accuracy: 0.2613 - loss: 1.4540 - val_accuracy: 0.3333 - val_loss: 1.1566
Epoch 6/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 416ms/step - accuracy: 0.3307 - loss: 1.1986 - val_accuracy: 0.3333 - val_loss: 1.1205
Epoch 7/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 6s 469ms/step - accuracy: 0.2717 - loss: 1.1653 - val_accuracy: 0.3333 - val_loss: 1.1031
Epoch 8/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 4s 419ms/step - accuracy: 0.2976 - loss: 1.1142 - val_accuracy: 0.3333 - val_loss: 1.1020
Epoch 9/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 475ms/step - accuracy: 0.3419 - loss: 1.1118 - val_accuracy: 0.3333 - val_loss: 1.1052
Epoch 10/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 451ms/step - accuracy: 0.2844 - loss: 1.1172 - val_accuracy: 0.3333 - val_loss: 1.1003
Epoch 11/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 4s 413ms/step - accuracy: 0.2900 - loss: 1.0960 - val_accuracy: 0.3333 - val_loss: 1.0989
Epoch 12/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 482ms/step - accuracy: 0.2906 - loss: 1.1124 - val_accuracy: 0.3333 - val_loss: 1.0991
Epoch 13/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 427ms/step - accuracy: 0.3107 - loss: 1.0990 - val_accuracy: 0.3333 - val_loss: 1.1000
Epoch 14/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 410ms/step - accuracy: 0.3365 - loss: 1.0943 - val_accuracy: 0.3333 - val_loss: 1.0989
Epoch 15/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 7s 594ms/step - accuracy: 0.2889 - loss: 1.1387 - val_accuracy: 0.3333 - val_loss: 1.1007
Epoch 16/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 9s 412ms/step - accuracy: 0.3293 - loss: 1.0971 - val_accuracy: 0.3333 - val_loss: 1.0991
Epoch 17/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 7s 545ms/step - accuracy: 0.2317 - loss: 1.1140 - val_accuracy: 0.3333 - val_loss: 1.0988
Epoch 18/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 4s 416ms/step - accuracy: 0.3924 - loss: 1.0962 - val_accuracy: 0.3333 - val_loss: 1.0990
Epoch 19/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 457ms/step - accuracy: 0.1874 - loss: 1.1234 - val_accuracy: 0.3333 - val_loss: 1.0993
Epoch 20/20
9/9 ━━━━━━━━━━━━━━━━━━━━ 5s 505ms/step - accuracy: 0.2015 - loss: 1.1130 - val_accuracy: 0.3333 - val_loss: 1.0998
```

Fig. 3: Data Training Process

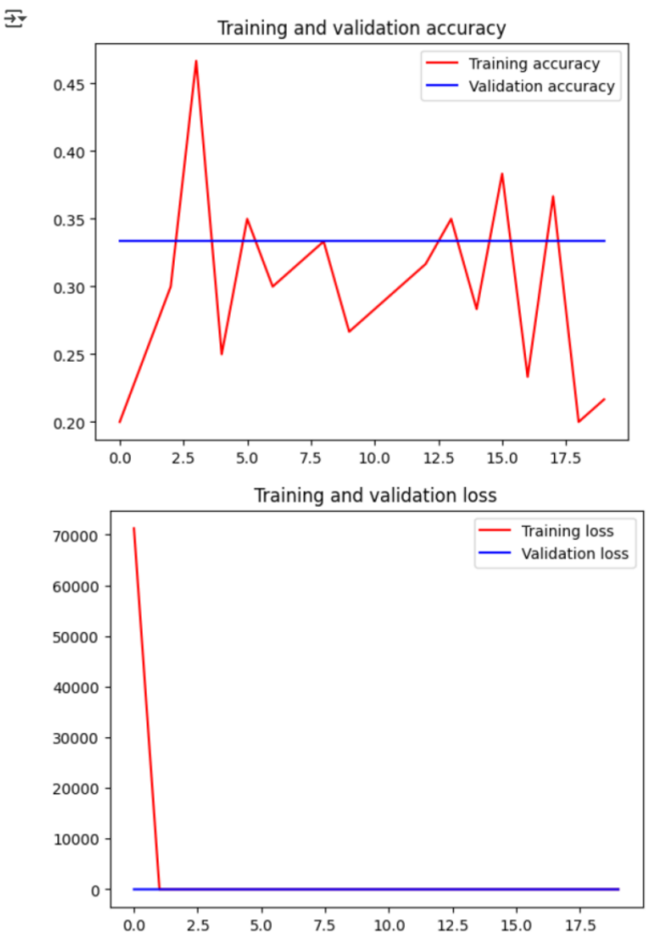


Fig. 4: Training Data and Accuracy Graph

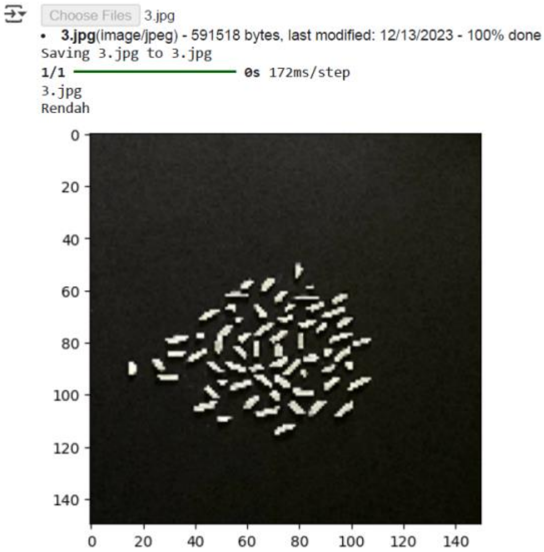


Fig. 5: Classification Results

The model was compiled using the categorical_crossentropy loss function, as this is a multi-class classification task. The Adam optimizer with a learning rate of 0.1 was used to help accelerate the convergence process. The model was then trained using the fit() method, with a batch generator from train_generator for training and val_generator for validation. The training runs for 20 epochs, with 9 steps per epoch and 1 validation step. In addition, a callback function called myCallback() was implemented to enable early stopping if the accuracy reaches a certain threshold. The use of verbose=1 ensures that the training process outputs detailed logs for performance monitoring during training. The extracted feature values from the rice image include: Red 164.7719, Green 68.3355, Blue 61.7290, Hue 0.4037, Saturation 0.6625, Value 0.6462, and an Area of 493,023 pixels, with a classification result of medium quality.

4. Conclusion

Based on the results of this study, several conclusions can be drawn:

a. The Convolutional Neural Network (CNN) method is capable of automatically classifying rice quality (premium, medium, and low) with high accuracy based on the visual features of rice images.
b. Google Colab enables efficient implementation of CNN models without requiring high-end hardware specifications, while also providing convenience in data processing, model training, and interface development using Python.
c. Data augmentation techniques such as rotation, flipping, and zooming were applied during pre-processing to improve model performance by increasing the variety of rice images in the training dataset.
d. The developed CNN model can be further improved using a larger dataset and additional optimization techniques to increase accuracy and expand classification coverage to a wider range of rice types.

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