

Classification of South Sulawesi Rice Quality Based on Website Using Machine Learning

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Abstract: Rice is a staple food commodity in Asian countries like Indonesia, but there are still challenges in quality assurance and standardization. The objectives of this research are to design and to develop a website-based system to classify the quality of rice using machine learning methods, to analyze the performance of the website-based South Sulawesi rice quality classification system, and to determine the accuracy of the classification system. This research uses the Convolutional Neural Network (CNN) method to classify rice quality based on some characteristics such as texture, shape, color, and size. The research succeeded in designing and developing a website-based system called "BERAS PINTAR". This system integrates a CNN model to classify 10 types of rice and three rice quality categories: premium, medium, and regular rice, based on input images of rice. Classification performance analysis shows very effective results. The model achieved an accuracy of 99.05% and was able to process classification quickly, proving its performance is satisfactory and functional. The resulting system proved accurate and efficient in identifying rice quality. The accuracy test reached a maximum of 100% and confidence levels ranging from 60% to 100%. This level of accuracy is consistent for rice varieties with distinctive visual characteristics.

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INTRODUCTION

Rice from South Sulawesi (Sulsel) is known as a staple food commodity characterized by high quality. Despite its significant potential, challenges remain to ensure the quality standard of rice on the market. Generally, visual-based rice quality classification process is not always objective and requires considerable time and effort (Alfi et al., 2023); (Dambe et al., 2023). The increasing market demand for high-quality rice needs the development of more objective and efficient rice quality classification methods. The application of data-based technology and algorithms can assist in classifying and assessing rice quality, increasing transparency in the trading process (Abidin et al., 2022). To achieve this, the application of digital technology can contribute to maintaining rice quality from upstream to downstream and better monitoring rice quality (Dambe et al., 2023), especially in facing global demands for high-standard and safe food products (Alfi et al., 2023). Through digital image processing and machine learning algorithms, more objective quality testing can be achieved compared to manual methods (Ardi et al., 2021). The use of neural network technology can reduce reliance on subjective human judgment and accelerate the classification process (Asnidar et al., 2023). This technological capability can ensure marketable rice quality and meet consumer expectations, thereby protecting the position of farmers and producers in a competitive market (Hendrival et al., 2022).

The development of a website-based classification system using machine learning technology is highly required. This system allows users to train a classification model using image data and to analyze visual features of rice, such as shape, size, color, and texture, which are important indicators of rice quality. The classification process is automated, reducing the uncertainty inherent in manual classification methods (Rajapaksha et al., 2023); (Mavaddati & Razavi, 2024).

The application of machine learning to classify agricultural commodities, including rice, can produce more accurate and reliable results. This method has demonstrated impressive accuracy rates, reaching approximately 99.0% (Altim et al., 2025). The combination of imaging and image processing techniques can be effectively used to identify and classify different rice variables with greater detail (Kurade et al., 2023). Classification systems using deep learning can achieve high accuracy and offer promising prospects for large-scale applications (Mavaddati & Razavi, 2024). This technology can ensure that marketed rice meets consumer expectations (Rita de Cássia Mota Monteiro et al., 2022); (Azmi et al., 2021).

The development of this website-based system is also expected to introduce more inclusive and accessible digital solutions to the people of South Sulawesi, especially in areas with limited technology. This important thing is that the agricultural sector, particularly rice, is a crucial component of the local economy (Pratama et al., 2023). Through this more accessible system, farmers and other business actors can easily adopt new technologies that assist them in classifying and assessing rice quality, thereby increasing the competitiveness of their products in both national and international markets (Pogonyshchev et al., 2022).

Digitalization in the agricultural sector is not only changing rice farming technically but also has significant social impacts. The use of digital technology can encourage active community participation in the production process, thus providing opportunities for local economic growth (Usenko et al., 2024). The adoption of digital technology in agricultural management can improve crop yields and product quality, ultimately contributing to food security (Salo et al., 2024). This system can also improve communication and create a good information network, in the exchange of knowledge and technology (Vardanyan et al., 2022). In the South Sulawesi region, where the agricultural sector remains the backbone of the economy, digitalization can help overcome challenges such as price fluctuations and quality risks of products distributed to the market (Winarni et al., 2023). By utilizing analytical data generated from this classification system, both the government and producers can make more informed decisions regarding agricultural development policies and strategies (Pogonyshchev et al., 2022); (Beksultanova et al., 2023).

The development of a website-based classification system not only aims to increase efficiency in the rice industry, but also has the potential to strengthen South Sulawesi's position as a rice production center in Indonesia, increase farmers' incomes, and support regional economic growth (Masri et al.,

2022). Through this technology, it is hoped that a system can be created that can classify rice and become a tool that can be used by farmers, entrepreneurs, and consumers to classify the quality of South Sulawesi rice automatically, with results that are more accurate, fast, cheap, transparent, and efficient compared to existing manual methods. Based on the explanation above, the objectives of this study are to design and develop a website-based system that is capable of classifying the quality of South Sulawesi rice using machine learning methods through the Teachable Machine platform on various physical parameters of rice, analyze the performance of the website-based South Sulawesi rice quality classification system, and determine the accuracy and efficiency of the website-based rice quality classification system in identifying rice quality on various physical parameters of rice.

METHOD

This study uses a Convolutional Neural Network (CNN) as a method for classifying rice quality based on digital images. CNN was chosen for their ability to automatically extract visual features (such as texture, shape, color, and size) from rice images, which are highly relevant for objective quality assessment. The data used were rice images; the study adopted a CNN-for-images (2D-CNN) architecture with the following main layers:

1. An input layer, which receives rice images in three-band (RGB) matrix format at a predetermined resolution.
2. A convolution layer (Conv2D), which applies a number of filters that are shifted across the image to detect local patterns such as grain edges, surface smoothness, or color variations. Each filter generates a feature map that highlights specific visual attributes.
3. A pooling layer (MaxPooling2D), which reduces the dimensionality of the feature map by taking the maximum value from each region, thereby reducing computational complexity while retaining the most dominant features.
4. A flatten layer converts the output of the convolution/pooling layer, which is a 2D matrix, into a 1D vector for processing by the fully connected layer.
5. A dense layer, where all neurons in this layer are connected to interpret the extracted feature combinations and map them to rice quality patterns (premium, medium, regular).
6. An output layer generates probabilities for each quality class using the softmax activation function, according to the multi-class classification used.

Model training was conducted using Google Teachable Machine Learning, which provides a visual interface for uploading rice image datasets, performing data augmentation (rotation, flipping, brightness changes), setting training parameters (epochs, batch size, learning rate), and exporting the model to TensorFlow.js format for website integration. The image data collection process involved extracting video frames of rice with various controlled backgrounds. Then, in the preprocessing stage, all images were standardized in size and augmented. Each image was labeled according to the type and quality of rice (premium, medium, regular). The data was then divided into training (80%), validation (10%), and test (10%) sets, and the model was evaluated using accuracy, loss, and confusion matrix metrics.

The training parameters used were Epochs: 50–100 iterations, Batch Size: 128, learning rate: 0.001, optimizer, and loss function. The use of 2D CNN can recognize local patterns of rice grains such as defects, density, and color, invariant to position where rice grains can be located anywhere in the image, efficient through parameter sharing mechanisms in convolutional layers and capable of processing large numbers of images. After the model is trained and converted to TensorFlow.js format, the model is integrated into a website that allows users to upload rice images and get quality classification results in real-time.

RESULT AND DISCUSSION

Result

The results of the website-based research to classify the quality of South Sulawesi rice using machine learning are described as follows:

1. Data Collection and Labeling

Data was collected on 10 types of rice: Head Rice, Santana Rice, Ramos Rice, Menir Rice, Red Rice, Sidrap Rice, Black Glutinous Rice, Red Glutinous Rice, White Glutinous Rice, and Regular White Glutinous Rice, obtained from traditional markets, for classification. After the rice was collected, it was labeled, distinguishing it into three grades: premium, medium, and regular. This served as a reference for the physical parameters such as rice name, rice quality, rice size, rice shape, rice color, and rice texture.

After labeling, initial video data was collected, with uniform lighting, consistent distance, and diverse backgrounds to minimize data collection bias. The videos were 30 seconds long per rice item, with 10 different colored backgrounds and a minimum resolution of 1080p.



Figure 1. Rice samples with different background.



Figure 2. images from video in JPG format

The data set is then uploaded to Teachable Machine to perform data augmentation such as rotation, flipping, and lighting changes to increase the diversity of the dataset without the need for additional data retrieval.

2. CNN Modeling using Teachable Machine

The platform to simplify the modeling and training process utilizes the Google Teachable Machine learning platform. The training process includes several convolutional, pooling, and fully connected layers. The training parameters include (1) Epochs, 50–100 training iterations to optimize accuracy, (2) Optimizer, Adam, or RMSprop to increase convergence speed. And (3) Loss Function: Categorical Crossentropy for multi-class classification. The data set is divided into 80% training data, 10% validation data, and 10% testing data. After the training process, new data is inputted in the form of file data input or data input from a camera connected to the device used. Based on this treatment, quite good and maximum results are obtained. In testing, this model is determined to be able to read new input data accurately, with varying levels of accuracy confidence with a maximum achievement of 100%. The variation in the model's confidence level from the reading results is determined by several factors, one of which is the color of the rice. Furthermore, the shape of glutinous rice has grains that are different from ordinary rice or have distinctive visual features, which allows for a high level of confidence in the model's test results. Furthermore, the number of input image datasets of rice types also has a significant impact.

3. Model Transferring

Model transferring is the compilation of a model that will be used for the data training process that will be used in the rice type classification process. In this compilation process, cross-entropy will also be performed to measure the accuracy parameters of the data to be trained, and this training model will be saved into a TensorFlow.js file (TensorFlowjs_converter). The previously trained model is exported from Teachable Machine in TensorFlow format. To enable integration and run on a web browser, the developed model is converted to TensorFlow.js format (TensorFlowjs_converter) through the TensorFlow library. Next, create the source code for the website. The following is a snippet of the source code: After the source code is complete, a preview is performed to ensure that the source code functions properly.

4. Website deploy dan Integration

Web development applies a web application obtained from the developer integrated with the source code resulting from training conducted on Teachable Machine previously. The website labeled "BERAS PINTAR" was developed with a maximum display for rice classification detection. The display of classifier results is based on the input provided. The input is in the form of an image inserted directly into the "BERAS PINTAR" website in the form of a JPG or PNG file. The rice type classification model created in the form of a web browser demonstrates the ability to determine the level of accuracy confidence for each type of rice tested accurately. The following is an image of one of the results of rice quality classification detection and its price on the "BERAS PINTAR" website which shows a 100% level of accuracy confidence for medium rice:

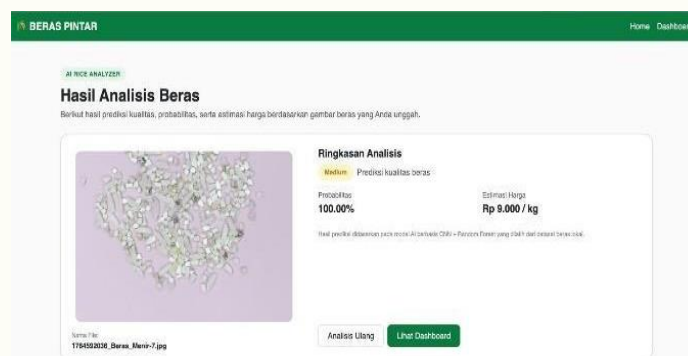
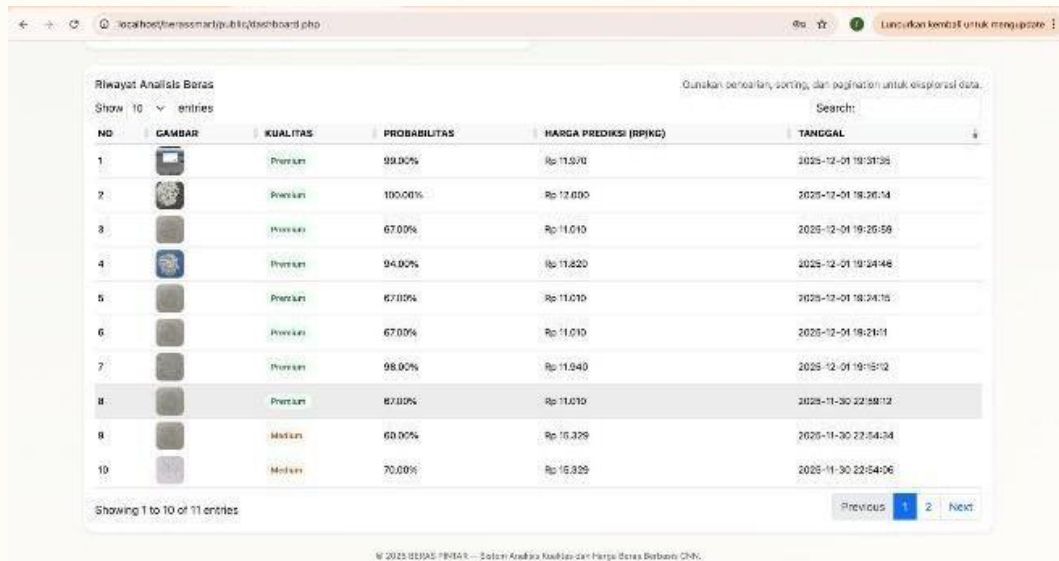


Figure 3. View of Rice classification result on web "BERAS PINTAR"

Based on the results obtained from the “BERAS PINTAR” website, the percentage of confidence in the accuracy of the test results ranges from 60% to 100%. The following is a screenshot of the results showing the percentage of results:



ID	GAMBAR	KUALITAS	PROBABILITAS	MARGA PREDIKSI (RP/KG)	TANGGAL
1		Premium	99.00%	Rp 11.570	2025-12-01 19:31:35
2		Premium	100.00%	Rp 12.090	2025-12-01 18:26:14
3		Premium	67.00%	Rp 11.010	2025-12-01 19:25:59
4		Premium	94.00%	Rp 11.820	2025-12-01 19:24:46
5		Premium	67.00%	Rp 11.010	2025-12-01 18:24:15
6		Premium	67.00%	Rp 11.010	2025-12-01 18:24:11
7		Premium	98.00%	Rp 11.940	2025-12-01 19:18:12
8		Premium	67.00%	Rp 11.010	2025-11-30 22:59:12
9		Medium	60.00%	Rp 15.329	2025-11-30 22:54:34
10		Medium	70.00%	Rp 15.329	2025-11-30 22:54:06

Figure 4. result of Percentage Web “BERAS PINTAR”

5. Research Analysis

The research aimed to classify 10 types of rice: Pandan Wangi Rice, Ramos Rice, Red Rice, Menir Rice, Sidrap Rice, Head Rice, Black Glutinous Rice, White Glutinous Rice, and Regular White Glutinous Rice. Classifying objects such as rice requires a training model to recognize each class of the object, specifically the rice type to be recognized. This object training process is carried out by creating a training model by building an artificial neural network (NN). The most commonly used NN network is the Convolutional Neural Network (CNN), which divides the captured image area into several sections to identify the most dominant object in that section of the image. This CNN method is very popular and has become an important part of the deep learning process in determining the class of an object. Objects with a predetermined class can be modeled so that the output of this training model is determined based on the desired number of classes. In this training modeling process, the training size of the images can be adjusted using the training batch size. The training estimation error can be minimized by adjusting the model's learning rate and the number of training sessions, depending on the number of training batches.

The model is trained using rice objects divided 50 epochs with a batch size of 32. The training process begins at epoch 1, which shows the lowest training accuracy of 0.621 with a loss value of 2.7283. This value continues to change in subsequent epochs, where accuracy increases while the training loss decreases. This also applies to the validation accuracy and loss values for the validation images, which are separate from the training images. The model's training accuracy and training loss persist until epoch 21, where the accuracy decreases from 0.9720 to 0.9640 in epoch 22, while the loss increases from 0.0793 to 0.1042 in the same epoch. This is typically caused by the training process attempting to adapt the object class training process to the increasing number of images and recognized objects to be trained again. Finally, at the final epoch of 50, the model achieved an accuracy of 0.9905 with a loss of 0.0328. An accuracy value above 99% indicates that the model can perform rice classification effectively and accurately. The results are shown in the following figure:

Epoch 1/50	
736/736 [=====]	- 317s 347ms/step - loss: 2.7283 - accuracy: 0.6211 - val_loss: 0.4001 - val_accuracy: 0.8601
Epoch 2/50	
736/736 [=====]	- 226s 306ms/step - loss: 0.3954 - accuracy: 0.8599 - val_loss: 0.3338 - val_accuracy: 0.9042
Epoch 3/50	
736/736 [=====]	- 203s 276ms/step - loss: 0.3100 - accuracy: 0.8959 - val_loss: 0.2439 - val_accuracy: 0.9188
Epoch 4/50	
736/736 [=====]	- 204s 277ms/step - loss: 0.2694 - accuracy: 0.9085 - val_loss: 0.3611 - val_accuracy: 0.8910
Epoch 5/50	
736/736 [=====]	- 206s 280ms/step - loss: 0.2435 - accuracy: 0.9163 - val_loss: 0.3178 - val_accuracy: 0.9120
Epoch 20/50	
696/696 [=====]	- 117s 167ms/step - loss: 0.1010 - accuracy: 0.9662 - val_loss: 0.3161 - val_accuracy: 0.9027
Epoch 21/50	
696/696 [=====]	- 116s 167ms/step - loss: 0.0793 - accuracy: 0.9720 - val_loss: 0.1486 - val_accuracy: 0.9583
Epoch 22/50	
696/696 [=====]	- 116s 166ms/step - loss: 0.1042 - accuracy: 0.9642 - val_loss: 0.0585 - val_accuracy: 0.9795
Epoch 23/50	
696/696 [=====]	- 117s 167ms/step - loss: 0.0885 - accuracy: 0.9697 - val_loss: 0.0485 - val_accuracy: 0.9856
Epoch 24/50	
696/696 [=====]	- 117s 168ms/step - loss: 0.0791 - accuracy: 0.9732 - val_loss: 0.0933 - val_accuracy: 0.9684
Epoch 25/50	
696/696 [=====]	- 116s 167ms/step - loss: 0.0792 - accuracy: 0.9741 - val_loss: 0.1156 - val_accuracy: 0.9573
736/736 [=====]	- 210s 285ms/step - loss: 0.1131 - accuracy: 0.9644 - val_loss: 0.2214 - val_accuracy: 0.9392
Epoch 43/50	
736/736 [=====]	- 211s 286ms/step - loss: 0.1069 - accuracy: 0.9639 - val_loss: 0.2362 - val_accuracy: 0.9375
Epoch 44/50	
736/736 [=====]	- 210s 286ms/step - loss: 0.1165 - accuracy: 0.9634 - val_loss: 0.1879 - val_accuracy: 0.9521
Epoch 45/50	
736/736 [=====]	- 210s 286ms/step - loss: 0.1022 - accuracy: 0.9643 - val_loss: 0.2648 - val_accuracy: 0.9399
Epoch 46/50	
736/736 [=====]	- 211s 286ms/step - loss: 0.1143 - accuracy: 0.9631 - val_loss: 0.3803 - val_accuracy: 0.9178
Epoch 47/50	
624/624 [=====]	- 108s 174ms/step - loss: 0.0239 - accuracy: 0.9919 - val_loss: 0.0456 - val_accuracy: 0.9864
Epoch 48/50	
624/624 [=====]	- 108s 173ms/step - loss: 0.0372 - accuracy: 0.9885 - val_loss: 0.0559 - val_accuracy: 0.9792
Epoch 49/50	
624/624 [=====]	- 109s 174ms/step - loss: 0.0119 - accuracy: 0.9958 - val_loss: 0.0624 - val_accuracy: 0.9812
Epoch 50/50	
624/624 [=====]	- 109s 175ms/step - loss: 0.0328 - accuracy: 0.9905 - val_loss: 0.0316 - val_accuracy: 0.9892

Figure 5. Result of Model Training

A significant increase in modeling accuracy and a decrease in modeling loss occurred between epochs 1 and 10. This is because in this phase the overall image can be recognized quickly within the range of this model's training epochs. In the following period, there will still be an increase in accuracy and a decrease in loss that is not too high. Ultimately, accuracy and loss will stagnate in the next epoch even though the number of epochs is increased. The following is a graphical image of the increase in accuracy and decrease in loss from the rice object classification training model with the number of epochs as follows:

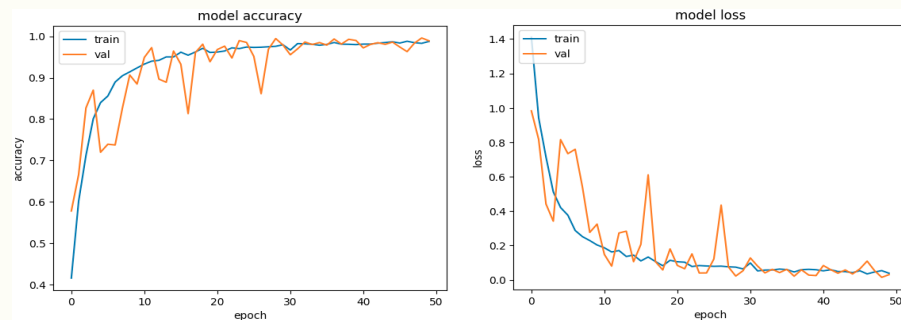


Figure 6. Model Accuracy and Loss during training

Evaluation of rice classification results using CNN using a performance matrix to gain a detailed understanding of accuracy values. This evaluation measures the performance of the developed model.

Classification Report:				
	precision	recall	f1-score	support
BerasKepala	0.99	0.99	0.99	08
BerasMenir	0.99	0.99	0.99	25
BerasMerah	0.95	0.96	0.95	08
BerasPandanWangi	0.96	0.96	0.96	58
BerasRamos	0.95	0.96	0.95	61
BerasSidrap	0.96	0.96	0.96	12
KetanHitam	0.95	0.95	0.95	23
KetanMerah	0.99	0.99	0.99	29
KetanPutih	0.99	0.99	0.99	17
KetanPutihBiasa	0.00	0.00	0.00	51
accuracy			0.99	2592
macro avg	0.96	0.96	0.96	2592
weighted avg	0.96	0.96	0.96	2592

Figure 7. Model Evaluation

Based on Figure 7 above, the classification of rice types using CNN demonstrated very high performance, with an average accuracy rate of 99%. The precision, recall, and f1-score metrics for all rice types showed excellent results. This indicates the model's ability to recognize classes and avoid misclassification. Overall, this model performed very well in rice type recognition.

Next, a confusion matrix was used to test the classification model and the object classification used, in this case, rice. This confusion matrix provides information on how well the model compares the predicted rice objects to the actual rice itself. Based on the confusion matrix results, it is clear that Ramos rice has a low predicted value compared to the actual rice, resulting in high prediction accuracy. Meanwhile, for other types of rice, improvements can be made by improving the image data, including image focus and lighting levels. The data used in this confusion matrix is random.

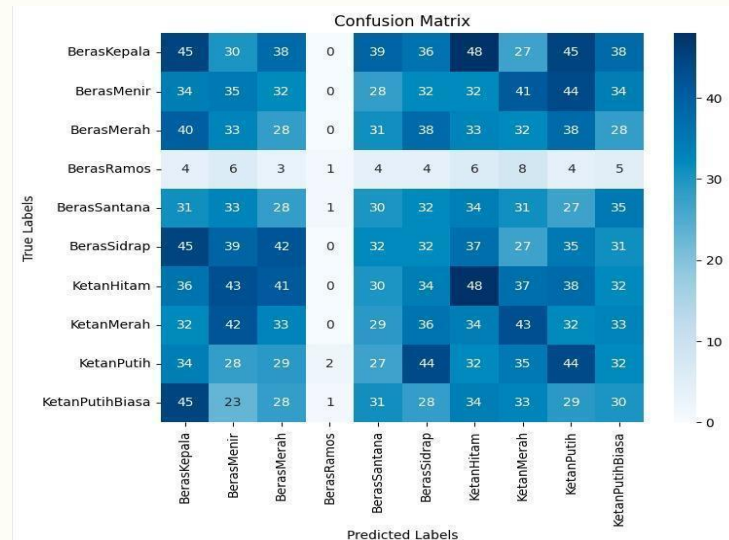


Figure 8. Confusion matrix of Classification model

As explained above, the overall application developed is quite accurate and reliable. It is based on input data of rice image files that can be classified well and accurately. The model then performs the classification process in real time. Classification results can be seen in the output for each classification text label, even though the input background color of each rice image is different. The higher the resulting percentage, the higher the classification accuracy. For all rice quality levels, this depends on the quality of the input image, including the lighting around the camera on the hardware used. Furthermore, the color of the rice and the shape of the grain structure, which have distinctive visual features, significantly influence the model's confidence level. Furthermore, the number of input rice image datasets also significantly influences the high level of confidence in the model's test results on the "BERAS PINTAR" website.

Some rice types have striking physical characteristics that are easily recognized by the model. Red rice and red glutinous rice have a contrasting dark red color, while black glutinous rice has a deep black color that is easily distinguishable. Santana rice has a very uniform grain shape, size, and texture. These unique characteristics allow the four types of rice to be recognized with near-perfect accuracy, even when the rice quality is medium or regular.

There are also types of rice that are more difficult to distinguish due to their more common or ordinary physical characteristics. Head Rice, Menir Rice, White Glutinous Rice, and similar types are generally white or cream in color. Although the model can still recognize these types with high accuracy, the classification results are more variable, especially if the rice is of ordinary quality, has a non-uniform size, or an inconsistent shape. The rice quality level also affects the model's accuracy. For good-quality rice with uniform grains, the model's accuracy is very high, sometimes reaching 100%. For medium-quality rice, accuracy remains high but decreases slightly due to small variations in color, size, or texture. For regular-quality rice, the model remains reliable in analyzing it. Rice types with strong

distinctive characteristics are still well recognized, while accuracy for types with ordinary characteristics varies more. The model is also able to identify changes in image backgrounds, such as blue, green, or brown. However, under certain conditions, such as light blue or dark brown backgrounds, the model's confidence level may decrease slightly for certain types of rice, particularly for ordinary rice.

Overall, this application is reliable. It can analyze images of rice taken directly or from photo files with various backgrounds. The application not only identifies the type and quality of rice (premium, medium, or ordinary) with high confidence but also calculates the percentage accuracy within a single classification. Thus, this model is fast, accurate, and ready for practical use.

Discussion

The research results demonstrate that this website-based rice quality classification system performs effectively. The model's 99% accuracy rate and real-time classification capabilities across various backgrounds indicate that the Convolutional Neural Network (CNN) model developed through the Teachable Machine platform successfully captured the key visual patterns of each rice type and quality. This finding aligns with current research trends, where CNNs are the primary architecture for rice image classification due to their ability to extract complex hierarchical features (Koklu et al., 2021); (Rani & Gupta, 2024). Recent research continues to develop and propose new CNN models specifically for this task (Singh et al., 2023).

This high accuracy is supported by a robust data collection strategy, which utilizes videos with controlled background variations, then extracted into thousands of images, providing a sufficiently diverse dataset for model training. Further augmentation processes such as rotation and flipping further strengthen the model's generalizability. This contribution is also significant in improving the overall performance of deep learning systems (Abdulkareem et al., 2024). Augmentation methods, including rotation, translation, and noise addition, have been shown to be effective in increasing the size of initially limited datasets, thereby reducing the risk of overfitting and improving classification accuracy (Abdusalomov et al., 2023); (Alshammari et al., 2024). Deep learning models trained with these augmentation steps can learn to recognize objects from different viewpoints, scales, and orientations, thereby improving the model's accuracy in recognition tasks (Abdulkareem et al., 2024); (Alshammari et al., 2024). Data quality in the context of CNNs cannot be ignored. A balanced dataset, with sufficient size and equipped with appropriate annotations, ensures that the model can learn well and produce accurate predictions (Isaiev & Kysil, 2024). Through the support of appropriate augmentation techniques, these models can achieve high performance, even in the context of initially limited and imbalanced data (Abdusalomov et al., 2023); (Motamed et al., 2021).

The varying confidence scores in the test results, ranging from 60% to 100%, reveal the dynamics and challenges of image-based classification. The model's very high and consistent performance for rice varieties with strong distinguishing characteristics, such as the deep red color of Red Rice and Red Glutinous Rice or the deep black color of Black Glutinous Rice, demonstrates that unique and contrasting visual features dominate the machine learning process. Similarly, the consistent grain shape and size of Santana Rice provide patterns that are easily and reliably recognized by the model. This aligns with the basic principles of computer pattern recognition, where features with high contrast and consistency are more easily separated in feature space. Research exploring feature recognition methods and improving model accuracy has been supported by the use of multi-scale techniques and the incorporation of various features, including texture and color, to achieve better classification results (Yang et al., 2023); (Wang et al., 2021). This suggests that to achieve more efficient and accurate classification results, it is essential for models to be trained on datasets rich in feature variation and including representative examples from each class (Sharma et al., 2022). Machine learning approaches, including CNNs, are highly effective in distinguishing cultivars with distinct visual characteristics (Sarkar et al., 2024).

On the other hand, the decreased confidence level and greater variation in results for rice varieties such as Head Rice, Menir Rice, and White Glutinous Rice highlight the limitations of models when

dealing with objects with generic visual characteristics. The predominant white or cream color, along with variations in shape and size—especially in regular quality or Menir Rice—create a gray area (ambiguity) in the classification process. Visual similarities between these types, such as between Santana, Sidrap, and Kepala rice, further complicate the model's task, especially when supported by an imbalanced number of data samples. This phenomenon is a reflection of data bias, where models tend to be more adept at classifying classes with greater data representation. Class imbalance in a dataset can significantly impact model performance, leading to a tendency for the model to prioritize more highly represented classes (Abdulkareem et al., 2024); (Abdusalomov et al., 2023). This strategy is crucial, as accurate classification is crucial for good results, and minimal data variation can lead to poor recognition.

The model's success in maintaining accuracy across a range of background colors, such as blue, green, and brown, demonstrates some robustness thanks to the data augmentation strategy. However, the slight decrease in confidence observed on certain backgrounds, such as light blue or dark brown, for some varieties of regular quality rice suggests that the interaction between object and background colors, as well as suboptimal lighting conditions, may still impact prediction stability. This challenge is exacerbated by the limitations of smartphone camera hardware in real-world settings, which can produce noisy, blurry, or unevenly lit images, creating a gap between controlled training data and field test data. The complexity of the analysis, which combines classification with quality assessment, also makes it more susceptible to interference from external factors (Lakshmi & Seetharaman, 2022). Approaches such as optimizing CNN architectures for greater lightness and efficiency (Deepika & Arunachalam, 2024) and Pathak et al., 2024) or utilizing transfer learning (Zheng & Sun, 2024) could be solutions to improve model performance and efficiency under suboptimal image input conditions. While the developed system has achieved impressive accuracy levels and performed reliably in controlled environments, its implementation in real-world scenarios requires attention to data preprocessing factors, input image quality, and potential biases in the dataset. The confidence levels generated by the model actually provide valuable information, not only as an indicator of accuracy, but also as a flag for ambiguous or out-of-distribution cases in the training data, thus providing a basis for user validation or re-checking. These results reinforce the finding that CNNs have great potential for precise rice classification (Rajora et al., 2024), but their accuracy is highly dependent on data quality and the match between training conditions and the application environment, a challenge also encountered in other image classification domains (Shinde et al., 2024).

CONCLUSION

Based on the results and discussion, the following conclusions can be drawn from this study to address all research objectives:

1. The website-based system "BERAS PINTAR" has been successfully designed and developed. This system integrates a Convolutional Neural Network (CNN) model built using the Teachable Machine platform. It functions to classify 10 types of South Sulawesi rice into three quality categories: premium, medium, and regular rice, based on the input of physical parameters in the form of images.
2. Analysis of the classification system's performance demonstrated highly effective and high results. The developed model achieved an accuracy of 0.9905 (99.05%) and was capable of processing classifications quickly (in real-time) within the website environment, demonstrating satisfactory and functional performance.
3. The resulting system proved accurate and efficient in identifying the quality of various types of rice. Test accuracy reached a maximum of 100% on new data, with a confidence level ranging from 60% to 100%. This level of accuracy is very consistent for rice types that have distinctive visual characteristics, confirming the great potential for efficient use of deep learning in the domain of rice quality classification.

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