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CLASSIFICATION OF RICE TEXTURE BASED ON RICE IMAGE USED THE CONVOLUTIONAL NEURAL NETWORK METHOD

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Abstract—*There are several types of rice that are commonly sold in rice stores. Many people, especially millennials, are not familiar with the different types of rice such as IR42 rice, Pera rice, sticky rice, and Pandan Wangi rice. Therefore, digital image processing techniques are needed to help analyze the types of rice to help people know what kind of rice they are going to buy at the market. The method commonly used in image processing for image classification is the convolutional neural network (CNN) method. Currently, CNN has shown the most significant results in image classification. This research used a dataset of 1560 rice images. The data was divided into two sets (training data and validation data) with an 80:20 ratio. The accuracy obtained by the CNN model using InceptionV3 for the rice data was 95.7% with a loss of 0.123. The Android application developed in this research achieved an accuracy of 83,4% based on the testing results calculated using the confusion matrix.*

Keywords: *android, classification, CNN, InceptionV3, rice.*

Intisari—*Ada beberapa jenis beras yang biasa dijual di toko beras. Saat ini banyak masyarakat khususnya generasi milenial yang belum mengenal berbagai jenis beras. Oleh karena itu, diperlukan teknik pengolahan citra digital untuk membantu menganalisis jenis-jenis beras. Metode yang umum digunakan dalam pengolahan citra untuk klasifikasi citra adalah metode convolutional neural network (CNN). Saat ini CNN telah menunjukkan hasil paling signifikan dalam klasifikasi gambar. Penelitian ini menggunakan dataset sebanyak 1560 citra padi. Data dibagi menjadi dua set (data pelatihan dan data validasi) dengan perbandingan 80:20. Akurasi yang diperoleh model CNN menggunakan InceptionV3 untuk data beras adalah 95,7% dengan loss 0,123. Aplikasi Android yang dikembangkan pada penelitian ini mencapai akurasi sebesar 83,4% berdasarkan hasil pengujian yang dihitung menggunakan confusion matrix.*

Kata Kunci: *android, klasifikasi, CNN, InceptionV3, beras.*

INTRODUCTION

Indonesia is one of the countries with the highest level of rice consumption per capita in the world. The reason for the high consumption of rice in Indonesia is due to the basic culture of eating rice in Indonesian society, where food is considered incomplete if there is no rice even though carbohydrate needs have been met through other food sources. Consumer demand in this case can vary from one individual to another. (Yusuf, et al., 2018). In rice shops, there are generally several varieties of rice that are often sold, such as IR42 rice, Pera rice, sticky rice, and Pandan Wangi rice. However, currently, there are still many people, especially millennials, who are not familiar with these various types of rice. Therefore, research was conducted to study and introduce various types of rice to the public (Ma'arif, et al., 2022). In classifying types of rice, humans have limitations in perceiving it through the sense of sight, considering the diversity of shapes and types of rice on the market (Emalia, 2020). Therefore, it is necessary to use digital image processing techniques to help analyze rice types more accurately (Trisnawan & Hariyanto, 2019). The method used is a convolutional neural network (CNN) with the InceptionV3 architecture (Nisa et al., 2020).

A convolutional neural network (CNN) is a method that is often used in image processing for image classification purposes (Saraswita & Sukemi, 2020). CNN is an algorithm belonging to the field of deep learning and is a development of the Multi-Layer Perceptron (MLP) model. Until now, the CNN method has shown very significant results in image classification (Kusumaningrum, 2018). In this era, smart devices such as smartphones have a very important role in everyday life (Fikri, 2023), especially Android-based smartphones. Android is a collection of software that includes an operating system, middleware, and major applications for mobile devices (Khairul, et al., 2018).

In research entitled Classification of Rice Varieties Using Artificial Intelligence Methods (Cinar & Koklu, 2019). Using a dataset taken by yourself using a box with a camera at the top so there is no light from outside and avoids shadows. The types of rice used were Osmanic and Cammco rice, each image of which was subjected to morphological feature extraction and obtained 7 features, namely area, perimeter, MajorAxisLength, MinorAxisLength, Eccentricity, convexArea and extent. With these features, models are created using LR, MLP, SVM, DT, RF, NB and k-NN machine learning techniques and performance measurement values are obtained. The success rate in classification was 93.02% (LR), 92.86% (MLP), 92.83% (SVM), 92.49% (DT), 92.39% (RF), 91.71% (NB), 88.58% (k-NN). If we look at the success rate results, it can be said that the research has achieved success.

Then from research entitled Classification of Rice Types Using the Convolutional Neural Network Method in MobileNET Architecture (Jauhari, 2022). The types of rice used in this research were IR64, sticky, basmathi, red and black rice. The entire dataset uses RGB color images (three color channels) and is resized to 224x224 pixels according to the input in the MobileNetV1 architecture. The training results of the MobileNet architecture on a good dataset is 1.0 and the validation accuracy value is around 0.9333. Meanwhile, in the bad dataset, the training accuracy was 1.0 and the validation accuracy value decreased to 0.6889. Then the training results on the Android device for each rice in 5 tests under 3 different light conditions, namely Basmathi Rice, Black Rice and Red Rice, achieved 100% accuracy in all light conditions. Rice IR 64 has accuracy results reaching 80% for white light, 60% for yellow light, and 100% for a mixture of white and yellow light. Glutinous Rice has accuracy results reaching 80% for white light, 100% for yellow light, and 80% for a mixture of white and yellow light.

Classifying types of rice with machine learning presents several challenges. One major hurdle is the quality and quantity of data, having insufficient or imbalanced data can lead to inaccurate results. Balancing model accuracy with interpretability, adapting to varying environmental conditions like lighting, and ensuring real-time processing and scalability are deployment challenges.

Those researches have shown that we can classify rice with images. With the advantages offered by Android smartphones and the Convolutional Neural Network (CNN) method, which is one method that is often used in image processing for image classification purposes (Peryanto et al., 2020), I plan to develop an Android-based application that can classify rice texture based on the image of the rice used with CNN and transfer learning from InceptionV3. Hypothetically this application will be able to run a machine learning model with a convolutional neural network method using transfer learning with the InceptionV3 architecture.

MATERIALS AND METHODS

The following is the framework for the research to be carried out:

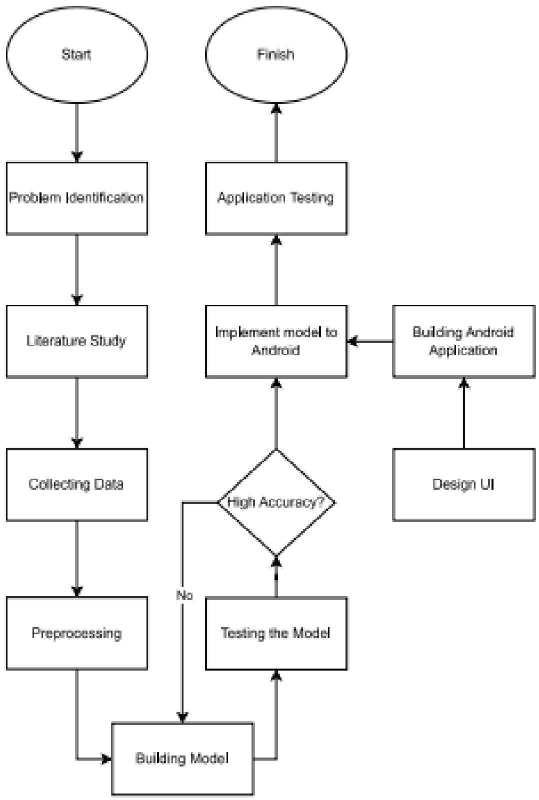

Figure 1. Research Design

Problem identification is the first stage carried out by researchers, namely classifying the texture of rice based on the rice used by distinguishing it into two classes, namely fluffier rice and pera rice. The literature study aims to study previous research that has the same topic as this research. In conducting this research, the author studied convolutional neural network methods, image classification, and Android application design from literature studies that she took.

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This research uses photographs for the data collection method. The image data used in this research was obtained and taken manually using a smartphone camera. Image data is taken by placing an object (rice) on a black base and then photographing it at a distance of approximately 25 cm. There are two classes of rice images, consisting of fluffier rice and pera rice. Sample data can be seen in the Figure 2. The images taken are equal to 780 images per class (pulen and pera), so the total dataset is 1560 images and the test data for the model testing and the application testing will be taken separately from those datasets.

Figure 2. Samples of Rice Images

For training data, 80% of the total images will be taken, and 20% will be used for evaluation data. Next, the training data will be resized. Resizing is carried out to equalize the size of the image to 480 x 480. The resulting image that has been equalized in size will undergo image augmentation such as rotation_range, width_shift_range, shear_range, horizontal_flip, vertical_flip, and fill_mode to increase data variations for model training. Next, the model was built using the transfer learning method with the InceptionV3 architecture (Tsang, n.d.) with weights from the Imagenet dataset.

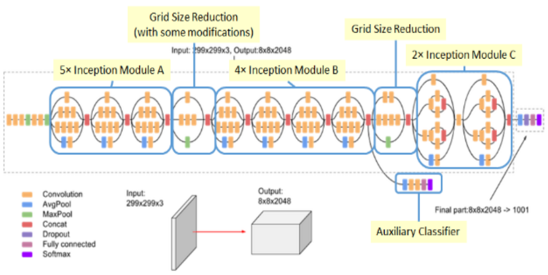

Figure 3. Inception V3 Architecture

An important part of InceptionV3 is the Inception module. This is a basic structure that allows feature extraction efficiently and at multiple scales. Each Inception module consists of several parallel convolution branches with different filter sizes, such as 1x1, 3x3, and 5x5 (Dahiya et al, 2020). The results of each branch are combined and passed to the next layer. This allows the network to capture patterns at different scales, making it highly effective for recognizing patterns in images of varying sizes. Also, pre-trained InceptionV3 models, trained on large datasets like ImageNet, are readily available. Transfer learning, where a pre-trained model is fine-tuned for a specific task with a smaller dataset, is a common practice (Raffel et al, 2020). Using a pre-trained InceptionV3 model as a starting point often results in faster and more accurate training for specific image classification tasks.

The model will train for approximately 50 epochs with a checkpointer. After that, model testing was carried out. Model testing is carried out with the same test data that has not been seen by either the model or the tester. The model that has been created will be tested for accuracy, recall, precision, and the f1-score of the convolutional neural network model that has been formed.

Then we start designing the interface of this application, which will be created using the Figma application. After making the design in Figma, the design will be made in Android using Android Studio with an XML base and the Kotlin programming language. This research was made based on Android, with Android Studio as the IDE and Kotlin as the programming language. The design stage for this application is represented using the unified modeling language (UML), which consists of use cases and activity diagrams.

After the model has been tested and the interface is complete, the model will be converted into TensorFlow Lite format, namely (.tflite), and quantization will be carried out, where the file size of the TensorFlow Lite model will be reduced. After that, use the extension from Android Studio to import the model into Android.

The final stage is application testing, which is carried out in real-time to obtain evidence that the application runs smoothly and the results of the classification match the scanned image.

RESULTS AND DISCUSSION

The data used in this research consists of images of fluffier rice and pera. The types of rice used for this research are those that are often sold in markets, namely fragrant pandan rice and ramos rice, which are representatives of fluffier rice. Meanwhile, for pera rice, use IR42 rice. Data collection was carried out by researchers by photographing rice in conditions with bright lighting, using a black base, with the rice object spread evenly, and with the camera height set at around 25 cm at a perpendicular angle to the rice object. The total data collected was 1560 images, consisting of 780 images of fluffier rice and 780 images of pera rice.

At the training stage, image preprocessing will be carried out, namely resizing, rescaling, rotation_range, width_shift_range, shear_range, horizontal_flip, vertical_flip, and fill_mode, in order to increase the variety of data to be trained.

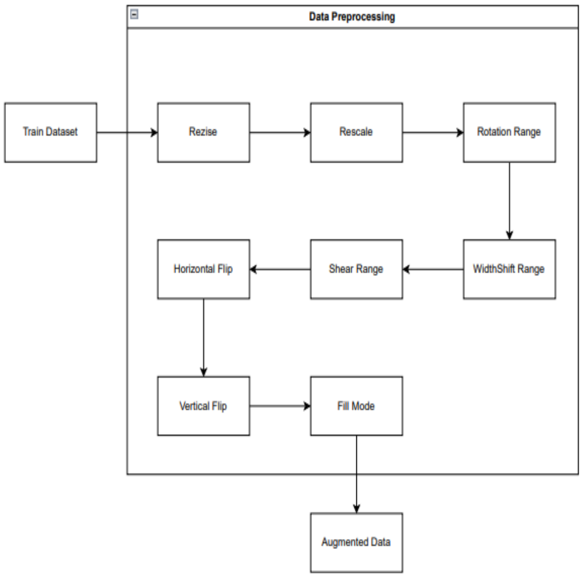

Figure 4. Data Preprocess

The dataset will change the size of the image to 480 x 480 pixels, then rotate it by 45 degrees, shift the width by 25%, tilt the image plane in the horizontal or vertical axis by 25%, flip the image horizontally and vertically, and fill in the pixel gaps automatically. whole to the nearest pixel.

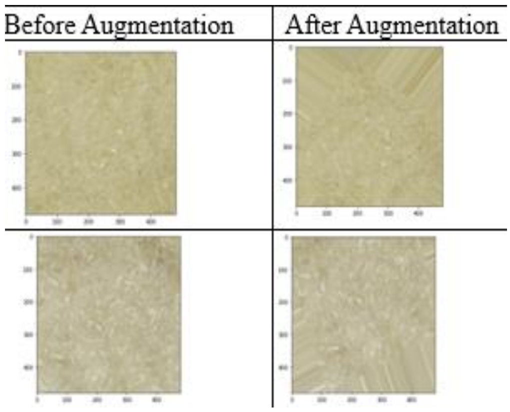

Figure 5. Results of Data Augmentation

Data augmentation here means that in the process of training, the dataset will have more varieties of images, such as flip, rotate, shift width, etc. So it will be more likely to learn the images with some noises inside.

The initial step in designing this model involves dividing the data into training and validation sets using an image data generator. In this stage, researchers divided the data in a ratio of 80% for training and 20% for validation, using a batch size of 8.

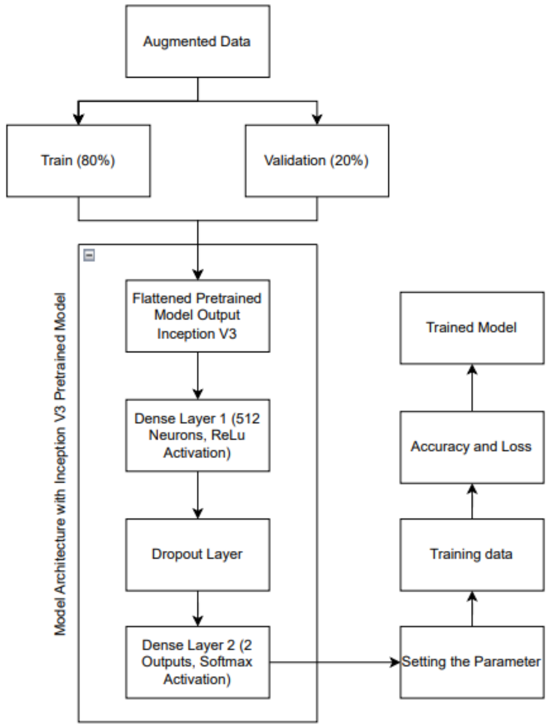

Figure 6. Model Architecture Design with Inception V3 Pre-trained Model

After a lot of trial and error, the researcher only added 2 dense layers and 1 dropout layer to the flattened pre-trained model output from Inception V3. This is because the pre-trained model itself already has good results because the weights that are in the pre-trained model using ImageNet dataset are helping the new model to learn new images. After that, the training process is carried out using a previously prepared model, with a total of 50 epochs. During the training, the process will stop if the accuracy reaches a value of 0.95 or more and the loss reaches a value of 2 or less. The model will be saved to the specified directory because the EarlyStop and ReduceLROnPlateau functions have been applied. After training was complete, the researcher visualized the training data, which included accuracy, val accuracy, loss, and val loss, to see the visualization of the model that had been trained.

The initial value of the training results with training data is good, namely 0.85 for training data and 0.75 for validation data. The training data continues to increase as the epoch progresses. The final value of accuracy for the training data is 0.957, and validation data accuracy is 0.878. Meanwhile, the loss graph obtained by the model also looks good from each epoch to a decrease, with the final result being that the loss for the training data is 0.122 and the loss for the validation data is 0.2822.

The model testing stage is carried out with a test dataset that is not included in the training process. There are 10 pictures, including 5 pictures of fluffier rice and 5 pictures of pera rice. The calculation results from testing 10 images, such as precision, recall, f1-score, and accuracy values, are all 0.8.

At this stage, the researcher used features from Android Studio, which can easily import Tflite models. Starting by creating a new folder containing the TensorFlow Lite model, we are given instructions on how to use the model. Instructions regarding using the model can be found in the models folder named'ml'.

After importing the model, the model can be used when the predict button is pressed. Therefore, it is necessary to create a function that will be executed when the button is pressed to make predictions and produce output in the form of classified types of rice. However, in order to classify the images, they must match the model's desired characteristics. Here, the model expects the image to be a tensor image with a size of 480x480x3.

The output of the model is a float array containing two numbers. Then create a function of the two numbers, whichever index is greater. If the 0th index is greater than the 1st index, then the rice is included in the soft rice category; if vice versa, then the rice is included in the fluffier rice category.

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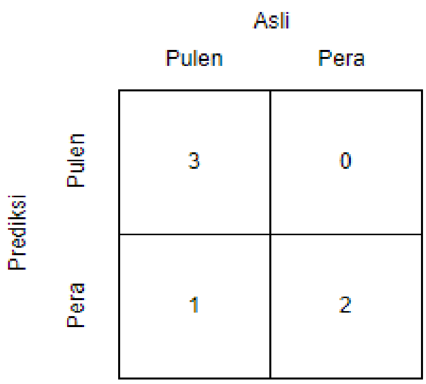

Figure 7 Confusion Matrix

From the test data carried out with real-time images, it can be calculated using a confusion matrix, such as

a. Precision

precision= TP/(TP+FP)…………………(1)
precision= 3/(3+1)
precision= 0.75

b. Recall

recall=TP/(TP+FN) ……………………..(2)
recall=3/(3+0)
recall=1.0

c. F1-Score

$$f1\ score = 2\ x\ \frac{precision\ x\ recall}{precision+recall} \text{……….(3)}$$

f1 score=2 x (0.75 x 0.75)/(0.75+0.75)
f1 score=0.857

d. Accuracy

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{……….(4)}$$

accuracy= (3+2)/(3+2+1+0)
accuracy= 0.834

CONCLUSION

Based on the analysis and discussion in the previous section, researchers can conclude that convolutional neural networks can be applied to rice images using new test data and produce a high level of accuracy using the InceptionV3-imagenet architecture. The experiments that have been carried out, showed that the amount of data, hidden layers, and dropout layers inside the model is significantly influence the results of the model created.

This research also revealed that the application developed was successful in using machine learning model and identifying both types of rice texture, namely fluffier and springier. The model accuracy for the training data is 0.957, and the validation data accuracy is 0.878. For the application, the accuracy is 0.834. Apart from that, this application also has a good prediction speed, which is around 1 second. In the experiments carried out, it was found that taking a good image for prediction means taking an image at a distance of about 5 cm from the object. Apart from that, the size of this application is also quite affordable, at only 224 megabytes, and it can be run on an Android cellphone with at least 3 GB of RAM.

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