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Increased Accuracy on Image Classification of Game Rock Paper Scissors using CNN

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Abstract

Pandemic COVID-19 made people unable to meet face-to-face and could only do traditional games virtually. One of the traditional games that have shifted into virtual games is the game of rock, scissors, and paper. In order to play virtually, a precise and accurate process of detecting the player's hand gestures is needed. This study aims to facilitate an image classification model with a higher level of accuracy than previous studies to distinguish hand gestures in the form of stone, paper, and scissors. Therefore, in this classification process, one of the methods of Deep Learning is used, namely Convolutional Neural Network (CNN). This research has a contribution in the form of adding epoch values and applying more in-depth hyperparameters to the CNN model. With more epochs and more in-depth hyperparameters, higher accuracy is obtained in detecting hand gestures in the form of stones, scissors, and paper. The dataset used in this study has the title "Rock-Paper-Scissors Images" totaling 2,188 which is divided into 3 classes, namely rock, paper, and scissors classes. This study increased the value of accuracy in previous studies with an increase in the average accuracy of previous studies from 97.66% to 99%.

Keywords: CNN, Deep Learning, Image Classification, Machine Learning, Neural Network

1. Introduction

As a result of the COVID-19 pandemic that has affected all regions of Indonesia, there has been a transition from traditional to virtual games. The global pandemic that began at the end of 2019 has caused people to follow social distancing regulations to restrict people's interactions with one another. It also influenced the development of traditional games around the world, especially in Indonesia. Children, in particular, might benefit from playing traditional games as a way to develop or improve their creativity. Children who previously engaged in active play with their friends experience a temporary disappearance of this culture or habit. The COVID-19 pandemic restricted face-to-face interaction and forced people to rely on virtual games for entertainment. One of the traditional games that have changed to become virtual is rock, scissors, and paper game. Players must perform a hand gesture detection method for any virtual games they play. The image classification approach is used to distinguish or detect hand motion patterns that symbolize rock, scissors, and paper in its implementation. In the game, machine learning is used to accomplish image classification. Machine learning is a technology that is widely used to replicate human behavior in solving a problem and emulating the human process of learning and generalizing [1].

The stage of image classification is necessary for the process of object detection, which in this case employs rock, scissors, and paper games. Methods such as Support Vector Machine (SVM) and Deep Learning (DL) can be employed in the process of classifying images to detect an object [2]. If the classification involves a large and complex dataset, Deep Learning is more suitable than a Support Vector Machine [3]. Deep learning is a subfield of machine learning that involves extracting characteristics or features, spotting patterns, and classifying data using several non-linear data processing layers. The concept of deep learning is to learn the features that exist in new data when similarities are found in old data or data that has been studied. Due to the addition of more layers, the studied model is more representative of the labeled image data. In machine learning, there are techniques for classifying images and detecting sounds by extracting features from the data, as well as special learning algorithms [4].

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Traditional machine learning and deep learning are built-in techniques for simulating the interplay between input and output in complex systems. In addition to having a higher-level structural hierarchy, deep learning differs from conventional machine learning in terms of learning objectives, model construction, and model training [5]. Deep learning itself is composed of a number of interconnected artificial neural networks, including CNN, RNN, LTSM, and SOM. Deep learning techniques can produce high-quality final results and save operational costs when handling data more effectively. Deep Learning can also be interpreted as a branch of Machine Learning which consists of high-level abstraction modeling algorithms on data using a set of non-linear transformation functions that are arranged layered and deep. Deep Learning is a perfect choice to be applied to supervised learning, unsupervised learning, and semi-supervised learning as well as for reinforcement learning in various applications such as image recognition, sound, text classification, etc. Basically, deep learning models are built based on artificial neural networks. Research has been going on since the 80s but recently it has revived thanks to computers that are getting faster, especially when it is coupled with technology in Big Data [6].

CNN or Convolutional Neural Network is a deep learning technology that plays a role in object recognition and classification. This is owing to the extensive usage of this technique in previous research and produces relevant findings in image classification [7]. The Convolutional Neural Network (CNN) was used for the implementation of plant classification research, with results suggesting that the CNN method performs classification better than the Support Vector Machine [7].

Convolutional Neural Network method, is a well-known image classification system since it is widely used in images [8]. CNN is a machine learning method that includes MLP (Multilayer Perceptron) development to transform data into two dimensions (2D). CNN has several layers, including input, output, and hidden layers, as well as convolutional, pooling, and fully connected layers [9]. Created in Japan, CNN was later improved upon by Yann LeCun throughout his research, and Alex Krizhevsky ultimately won the ImageNet Large Scale Visual Recognition Challenge by using CNN, demonstrating CNN's superiority to other methods for classifying objects in images. The idea for CNN is based on the biological nervous system and described as a convolution that unifies many layers with parts that operate in parallel [10].

CNN has evolved as a major approach used in the classification process based on contextual information. CNN has a remarkable capacity for learning contextual features, which enables it to address pixel-related issues [5]. Aside from image classification, CNN is employed in a variety of other fields due to its greater performance and outcomes, including object identification, face detection, speech recognition, diabetic retinopathy, facial expression recognition, etc [11].

The use of image classification with CNN is employed in several crucial fields, such as the health industry, where studies on the classification of lung diseases using X-ray images have shown fairly promising outcomes [12], Another evidence of this research is the eye disease classification study accuracy value, which had an accuracy result of 98.37% and was considered as an excellent result [13].

For instance, in the agriculture industry, digital image classification research on spices and herbs produced generally positive findings with a calculation of accuracy in training data accuracy of 0.98 and testing data accuracy of 0.85 [14], Another example came from research on disease detection in plant leaves with image classification using CNN, which inferred based on model installation and testing of leaf data obtains positive outcomes [15].

Furthermore, image classification with CNN may apply in non-essential areas including the cultural sector, such as image classification on *batik* motifs, which generates satisfactory results [16], Other research in the cultural area, such as image classification on *wayang*, has shown that CNN can deliver excellent results based on test data [4].

There are various prominent image classification algorithms, including SVM, KNN, and CNN. When the three algorithms are evaluated in terms of weather image classification research, the CNN algorithm produces the best results [17].

In contrast to other algorithms, CNN may investigate unsupervised as a feature without being specified beforehand, which is another benefit of the method. CNN also adds preprocessing to convolution to obtain an implicit characteristic in an image [18]. These advantages of CNN have shown to be quite ideal for image classification, particularly in the classification of images from rock, scissors, and paper games.

In rock, paper, and scissors game, the human hand makes a variety of gestures to describe the shapes of rock, paper, and scissors. This is one of the games distinctive applications of human hand gestures. Convolutional steps on CNN can perform image extraction automatically; for example, in this study, one of the features that extracted is the edge of the hand. The classification of Rock Paper Scissors hand motions using an Epoch value of 50 and the VGG architecture obtained an accuracy of 81.53% in a previous study with the CNN method on rock, scissors, and paper images by Thema et al [19]. Furthermore, Naufal et al. found that the accuracy of their classification of images from the rock, scissors, and paper game using the Epoch

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value of 10 was 97.66% [2]. According to previous studies, CNN offers a high level of accuracy for the detection and recognition of features regardless of the position of the object in the image, however, the application of the epoch is still limited, and the layer applied itself is categorized as missing in detail or lacking in detail although the degree of accuracy may still be maximized. It improved further by extending the epoch data training and developing a more detailed architectural model with the additional layer. It is possible to deduce that the gap is the lack of epoch and CNN architectural layers for the classification of rock, scissors, and paper game images.

The implementation of this research uses a particular type of deep learning algorithm, called CNN or Convolutional Neural Network, which may help in detection by classifying datasets in the form of hand gestures to differentiate which are rock, paper, and scissor. The purpose of this study is to improve accuracy by using a higher epoch value and assembling a more in-depth model architecture based on previous research [2]. The stages of this research include gathering or accumulating datasets, developing an architecture for CNN testing, and computing or calculating performance.

2. Research Methods

To analyze the degree of accuracy in the image classification of the research sample, which consists of hand gesture image data, this research uses research objects from the rock, scissors, and paper game. These objects each represent the shape of a rock, scissor, and paper using the CNN (Convolutional Neural Network) method. The stages of the research method used in this research are depicted in Figure 1 and involve 5 steps: gathering or accumulating datasets; splitting data; preprocessing; creating CNN model; and calculating performance [2].

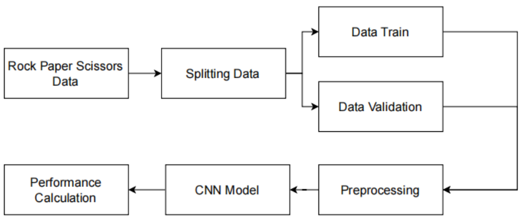

Figure 1. Research Steps

2.1. Dataset

The dataset for this study was taken from Kaggle under the title "Rock-Paper-Scissors Images" revealed on page [20]. The dataset consists of hand gestures resembling stones, scissors, and paper. The dataset is divided into three folders: rock, paper, and scissors. The folder rock has 726 data, the paper has 712 data, and the scissors have 750 data. Table 1 gives the dataset specifics for each class. Figure 2 depicts an example of a dataset from the rock, paper, and scissors classes used in the study.

Table 1. Details of the Dataset on Each Class

Class	Total
Rock	726
Paper	712
Scissors	750

Figure 2. Sample of Research Dataset

2.2. Splitting Data

In this study, the dataset is divided into two categories: train data and validation data. The train data accounts for up to 80% of the dataset, while the validation data accounts for 20% of the remaining dataset, which contains 1751 train data and 437 validation data. Table 2 describes the dataset separation in each class.

Table 2. Details of Splitting Dataset of Each Class into Train and Validation

Class	Train	Validation
Rock	584	142
Paper	567	145
Scissors	600	150

2.3. Preprocessing

Data preprocessing is performed before training. Its purpose is to convert raw data into prepared, structured, and useable data [21]. Details of preprocessing shown by Table 3.

Table 3. Data *Preprocessing*

Data	Description	Total
Train	target_size = (100,150), batch_size = 32, class_mode = ‘categorial’, subset = ‘training’	1751
Validation	target_size = (100,150), batch_size = 32, class_mode = ‘categorial’, subset = ‘validation’	437

2.4. CNN Model

This level is completed through pooling. Pooling is a technique for deciphering information in an image while features are being checked and maintained [22].

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Pooling is used to accelerate computation, making it easier to identify and making the model more resilient. [23].

Table 4. Details Hyperparameter on CNN Model

Layer	Output Shape	Description	Output Shape
Conv2D	(None, 98, 148, 16)	filters=16, kernel_size=3, strides=3, input_shape = (100,150,3), activation=relu	448
MaxPool2D	(None, 49, 74, 16)	pool_size=2, padding=same	0
Dropout	(None, 49, 74, 16)	pool_size=2, padding=same	0
Conv2D	(None, 47, 72, 16)	filters=16, kernel_size=3, strides=1, padding=same, activation=relu	2320
MaxPool2D	(None, 23, 36, 16)	pool_size=2, padding=same	0
Dropout	(None, 23, 36, 16)	pool_size=0	0
Conv2D	(None, 38, 38, 64)	filters=32, kernel_size=3, strides=1, padding=same, activation=relu	4640
MaxPool2D	(None, 10, 17, 32)	pool_size=2, padding=same	0
Dropout	(None, 10, 17, 32)	pool_size=0	0
Flatten	(None, 5440)	-	0
Dense	(None, 64)	hidden layer=64, activation=relu	348224
Dropout	(None, 64)	pool_size=0, padding=same	0
Dense	(None, 3)	neuron=3, activation=softmax	195

According to Table 4, layer 1 has 16 output shapes with 3 filtering steps for each step and a 100x150 input layer. Then, for the activation function, add ReLu (rectified linear unit). Max-pooling is used on the next layer to reduce overfitting. [24]. This is repeated three times by raising the filter value from 16 to 32. Flatten layers are used because the input is fully connected layers [25]. After that, compress the concealed layer by 64 units. The last layer employs softmax activation since it is one of the better activations for binary cross entropy throughout the model compile process. [4]. This layer comprises 3 output neurons with the values 0-2, where 0 represents class paper, 1 represents class rock, and 2 represents scissors. The softmax activation function with X as input is shown in Formula 1, and the ReLu function with z as input is shown in Formula 2.

$$\sigma(x) = \frac{1}{(1+e^{-x})} \quad (1)$$

$$R(z) = (0, z) \quad (2)$$

To optimize the accuracy of the data training step, the study applied 100 epochs and 32 batch sizes. The parameters involved in the training data are detailed in Table 5. The optimizer applied is Adam using a learning rate of 0.001 then the model is stored in metric accuracy. Adam is used as an optimization method due to its simple implementation, static learning rate, adaptability, and ability to obtain good and rapid results. [26]. Then, for optimization of the fully-connected layer on CNN, binary *crossentropy* is used as a loss function of the data parameters.

Table 5. Training Parameters

Parameter	Value
Optimizer	Adam
Loss Function	Binary Crossentropy
Batch Size	32
Optimizer Metrics	Accuracy
Learning Rate	0.001
Epochs	100

2.4. Performance Calculation

The model's performance is calculated using four parameters, represented by a confusion matrix: Metric Accuracy, F1 Score, Precision, and Recall [27]. The formulas from 3 to 6 calculate each parameter of the performance calculation procedure, where TN indicates True Negative, FN indicates False Negative, FP indicates False Positive, and TP is True Positive [28]. Accuracy is a description of the model's reliability in accurately classifying the model [29]. Precision compares the accuracy of the data presented with the model's predictions [16]. Recall offers information about the model's success in displaying information from the model [30]. The F1 Score is the average data result from the comparison of precision and recall [31].

$$F1\ Score = \frac{Precision\ x\ Recall}{Precision + Recall} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$Accuracy = \frac{TP+TN}{TP + TN + FP + FN} \quad (6)$$

3. Results and Discussions

After performing different stages of the previously used methods, the performance calculations' findings are displayed in Table 6, where the average accuracy of 99% indicates excellent results in image classification research on rock, paper, and scissor images.

Table 6. Performance Data

Data	Accuracy	Precision	Recall	F1 Score
Rock	0.99	0.97	0.99	0.98
Paper	0.99	1.00	0.97	0.99
Scissors	0.99	0.99	1.00	1.00

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Each epoch procedure requires an accuracy plot and loss plot analysis. The model developed throughout the training phase is put to the test for data validation. An accuracy comparison between data train and validation is necessary to determine whether the model is overfitting. If there is a significant difference, the model then considered overfitting. Table 7 illustrated the average accuracy comparison in research [2] with this research. This research reveals an increase in accuracy. The increase was caused by the use of 10 times more epoch values in the training than in the previous study. Furthermore, an increase happened as a result of the development of the CNN hyperparameter that was applied more thoroughly, for example, the filtering process in Max-Pooling occurred 3 times, which seeks to reduce over-fitting and optimize the accuracy Using the most accurate values in the comparison of three output neurons, the anticipated value = 0 is paper, 1 is stone, and therefore other objects suggest the image is scissors. Figure 3 depicts a graph accuracy plot and loss plot for each epoch, while Figure 4 illustrates the prediction results for the rock, scissors, and paper hand gestures consecutively.

Table 7. Comparison of the Average Accuracy on Previous Studies

Data	Previous Studies [2]	Latest Studies
Accuracy	0.9766	0.9931
Precision	0.9782	0.9943
Recall	0.9766	0.9966
F1 Score	0.9760	0.9989

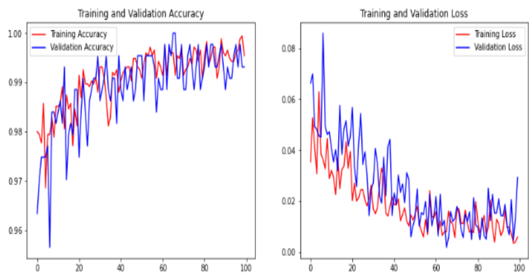

Figure 3. *Accuracy Plot* and *Loss Plot*

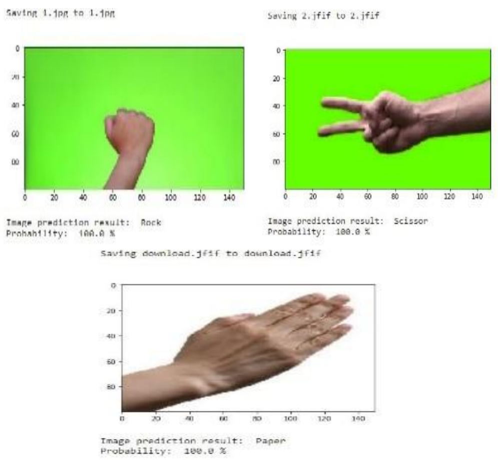

Figure 4. Prediction Results on Rock, Paper, and Scissors

4. Conclusion

All of the datasets used in this research consist of a collection of hand gesture data in the form of stones, scissors, and paper that transformed into training data and validation data. Based on the calculations and experiments findings, it can be concluded that the implementation of CNN for image classification illustrated excellent results in the classification of rock, scissors, and paper game images as evidenced by the results of the average accuracy from previous studies, which was 97.66% to 99%, and also proven to have better performance than previous research due to the more detailed data training process by giving the Epoch value of 100, along with model formation by adding a deeper architectural layer. The research model is anticipated to be used in a virtual version of the rock, scissors, and paper game with a camera. For future studies, the authors recommend using a higher Epoch value and applying transfer learning to achieve optimal efficiency and rapid training data processing.

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