VGG-16 Accuracy Optimization for Fingerprint Pattern Imager Classification

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***Abstract*— A fingerprint is a unique biometric identity commonly used as evidence in court. However, the quality of fingerprints can deteriorate due to external factors such as uneven surfaces, weather conditions, or distortion. This study uses the FVC2000 dataset and applies Convolutional Neural Networks (CNNs) to enhance and classify fingerprint images, focusing on patterns such as arches, loops, radial loops, ulnar loops, and twin loops. A novel aspect of this research is the optimization of the VGG-16 model by making specific adjustments to the hyperparameters, including setting the learning rate to 0.0001, using 50 epochs, and selecting a training-to-validation data split of 80%:10%. These adjustments were made to enhance the model's ability to classify complex and varied fingerprint patterns, which typically present challenges to standard CNN models. The results of the study show the highest accuracy of 100% on the test data with the optimized parameters.These findings demonstrate that the optimized VGG-16 model successfully classifies fingerprint images with optimal performance. The real-world implications of achieving 100% accuracy include an increase in the reliability of biometric identification systems, especially for forensic and security applications that require high accuracy to ensure accurate decisions. This study makes a significant contribution to the development of CNN-based fingerprint classification systems, offering a new approach that supports more reliable and precise biometric applications.**

Keywords*— *Fingerprint, Optimization, Classification, VGG-16. CNN

I. INTRODUCTION

Modernization in countries like Indonesia brings changes in customs, culture, and mindset. These changes can lead to both positive and negative effects, such as economic inequality, crime, and juvenile delinquency. Crime can be influenced by internal factors, like age, gender, education, and mentality, as well as external factors, such as time, place, and family conditions. One serious crime is murder, which causes both psychological and material harm. The police investigate to identify the perpetrators of such crimes. [1][2]

Fingerprint pattern identification is a very important aspect in the process of recognizing a person's identity. Fingerprints can also be valid physical evidence and be recognized in legal proceedings in court. However, fingerprint images found at crime scenes (crime scenes) often deteriorate in quality due to various factors. These factors include distortion due to being touched by another party, partially erased patterns, or skin conditions that have experienced wrinkles. [3][4]

To overcome this problem, efforts are needed to improve the quality of fingerprint images so that they can be processed and analyzed better. One effective method for improving image quality and classifying fingerprint patterns is the Convolutional Neural Network (CNN). This method is part of artificial intelligence (AI) that utilizes deep learning to analyze images with a high degree of accuracy. CNNs allow the analysis of fingerprint patterns even though the imagery is of poor quality due to conditions in the field. Thus, the application of CNNs can improve accuracy in the fingerprint identification process, which ultimately helps in the forensic investigation process.[5][6]

In the context of forensics, digital image processing plays a very important role. This processing not only increases the efficiency of law enforcement officials in obtaining more accurate evidence, but can also reduce the potential for errors in the judicial process. Through technologies such as CNNs, fingerprint image processing has become more sophisticated, resulting in more reliable and reliable results. [7][8][9][10]

CNN is a deep learning method inspired by how human brain cells function. It is effective for object classification, especially with large amounts of data. CNNs work by extracting and processing features from input images through multiple layers of neurons. This creates a more informative representation, making classification easier. [11][12][13]

In this study, the CNN method with the VGG-16 architecture will be used, an architecture that has been proven to be reliable in image analysis. To optimize its performance, some important parameters will be adjusted. These settings include:

1. The ratio of training data sharing and validation data to determine the optimal data composition.
2. The weight of the epoch value, which will be set to find the best number of epochs to improve the model's ability to generalize.
3. Learning rate, which is a parameter that controls how much

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the model changes its weight during the training process.

In addition, this study will involve various experimental scenarios to test the influence of each parameter on the performance of the CNN model. The results of this experiment are expected to determine the most optimal configuration in improving the accuracy of fingerprint pattern classification. With this research, it is hoped that CNN-based deep learning technology can further contribute to supporting forensic efforts and improving justice in the legal process.

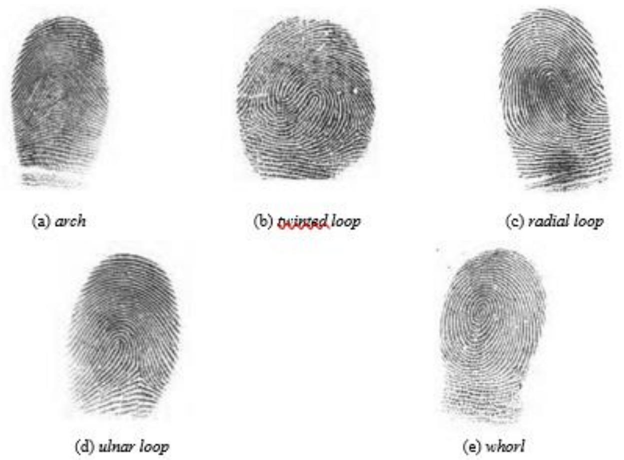

Fig. 1. Types of Fingerprint Image Patterns

Hadaris and Arisy Nabawai explained that dactyloscopy comes from two words in Greek, namely [6]*daktulos*, which means finger line, and *scopeoo*, which means to observe fingers. Therefore, it can be concluded that dactyloscopy is a science that develops the recognition of a person's identity through the observation of the unique pattern of fingerprint strokes found on the fingers and soles of the feet.

The fingerprint used in the identification process is a latent fingerprint obtained from the result of a reproduction that is deliberately taken or stamped with special ink left on an object that has been touched by the skin of the fingers or the soles of the feet. The selection of fingerprints is based on three axioms, namely:

1. Each pattern of a person's fingerprint has unique traits and different physical characteristics in each individual, so it will never be the same as the pattern belonging to another individual.

2. The fingerprint pattern begins to form from the time the fetus is approximately 120 (one hundred and twenty) days old in the womb and will not change until death.

3. Fingerprint strokes can be formulated based on several parameters, such as *core location*, *delta*, *ridge counting*, and *ridge tracing*, thus forming the formula for each fingerprint.

Every individual, whether human, animal, or other living beings, has a unique fingerprint. No two fingerprints are exactly the same, and they remain unchanged throughout life. Fingerprints begin to form around four months of age and continue to grow and change as we age. To capture latent fingerprint patterns, methods like applying oil, amino acid liquid, paint, blood, or nanomaterials are used on the surface, then transferred to paper or plastic.[14][15][16]

There are four main types of fingerprint patterns: ulnar and radial loops, whorls, arches, and tented arches. An arch has a raised center line that forms a slight outward curve. A whorl forms a circular pattern, while a loop creates a curved line that starts and ends on the same side. The point where lines meet in a loop is called the triradius.[2]

Based on the background discussed, this study will perform fingerprint pattern classification using the VGG-16 architecture method with five types of fingerprint patterns as output, namely arch, ulnar loop, radial loop, whorl, and twinned loop.

II. RESEARCH METHODS

This study proposes a fingerprint pattern image classification method using Convolutional Neural Network (CNN) with VGG-16 architecture. The fingerprint images in *.jpg format with dimensions of 256x256 pixels were obtained from the FVC 2000 Database (Fingerprint Verification and Competition). In the training process, fingerprint images will go through several stages, ranging from convolutional layers, max collection layers, dropouts, flattens, to solid layers, with the final output in the form of a classification of 5 types of fingerprint image patterns. Each stage in the CNN network serves to extract features from the image and improve the model's accuracy in recognizing fingerprint patterns. For more details, the flow diagram of this proposed method can be seen in Figures 2 and 3. [17][18]

Convolutional Neural Network (CNN) is a type of deep feed-forward artificial neural network architecture, by maintaining a hierarchical spatial structure to study the representation of internal features in processing grid data (such as images) and pattern recognition. CNNs are designed automatically from the input data through a convolution layer that serves to detect local features, such as edges, angles, or texture patterns in the image. CNNs also have a hidden layer that is only implicitly connected to a subset of neurons in the previous layer.[19]

[20] CNNs have three main types of layers, namely convolutional layers, pooling layers, and fully-connected layers. This architecture results in the extraction of hierarchical features or filters that have a specific purpose. Generally, the first layer is focused on identifying edges or color fluctuations, the second layer is used for shape identification, the next layer is used to study partial parts of the object, and the last layer is used for the identification of the object as a whole

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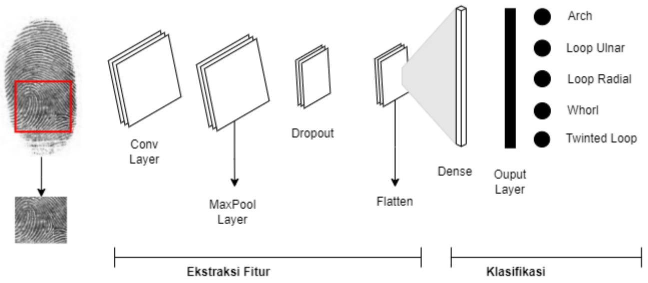

Fig. 2. VGG-16 Architecture Proposal

Based on the image 2, This method uses two stages of processing, namely feature extraction and classification. In the feature extraction process, this stage is responsible for retrieving important information from the input image, i.e. fingerprints. The fingerprint will pass through the first layer, the convolutional layer, which is responsible for picking up local features from the fingerprint image, such as a line or arch pattern. Furthermore, the max pooling layer is used to reduce the dimension of the feature, so that important information is preserved and the data size is reduced. Meanwhile, the dropout layer is used to prevent overfitting and convert the data to a one-dimensional size, which will be processed on a flattened or fully connected layer. The classification process is responsible for classifying the features that have been extracted into one of several fingerprint classes. The dense layer is the fully connected layer that connects all the neurons of the Flatten layer. The output layer is in charge of providing the final result of the classification. Each neuron in this layer represents a class of fingerprints. The fingerprint class consists of five types that are the target of classification, namely arch, ulnar loop, radial loop, whorl, and twinted loop. Of course, each class has a different pattern and is recognized based on the characteristics of each pattern. [21]

This architecture used in his research was explained to be able to achieve a high level of accuracy in the classification of image objects and tends to be very simple. There are several key features in this architecture:[18]

1. The layers in this architecture amount to 16 layers of convolution.
2. The processed kernel is 3x3 in size so there are not many parameters used.
3. In the feature map process, this architecture uses a 2x2 max pooling layer with 2 stride which of course facilitates the classification process and saves time.
4. Using ReLu on the input and output processes using softmax.

[22]Feature extraction is a technique to obtain features and datasets that are used for the storage of fingerprint pattern data later. Feature extraction on CNN consists of two layers, namely convolutional and sub-sampling which have hyperparameters, for hyperparameters applied to the CNN model of the VGG-16 architecture type can be seen in table 1 which is processed at the confiq stage to set all the parameters used in the built model.[23][24]

Table I. Architectural Parameters of VGG-16

Layer	Output Form	Param
VGG16	(7, 7, 512)	14.714.688
conv2d	(7, 7, 32)	147.488
max_pooling2d	(3, 3, 32)	0
Dropouts	(3, 3, 32)	0
flatten	(none, 288)	0
dense	(none, 5)	1.445

In the table 1, VGG 16 is a CNN architecture consisting of 16 layers that utilize transfer learning. The base layer of this VGG-16 model has dimensions of 7x7 with 512 channels. After extraction, it is followed by a convolution layer that has 32 filters for further processing. MaxPooling was used to reduce the spatial dimension from 7x7 to 3x3 while retaining 32 filters. Dropouts are used to prevent overfitting. In the Flatten layer, the data is converted from a 3x3x32 shape to a one-dimensional shape with 288 units. Dense is a fully connected layer that has 5 outputs in the form of a fingerprint image pattern class. [25]

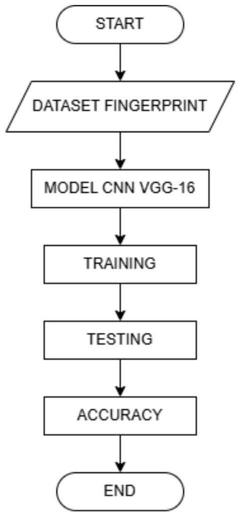

Fig. 3. Flowchart training & testing model

Based on image 3, The flowchart shown shows the steps in the fingerprint pattern recognition process using the Convolutional Neural Network (CNN) method with VGG-16 architecture. Here is an explanation of the steps on the method:

1. At the dataset stage, fingerprints are collected. This dataset can be a fingerprint image of various patterns (loops, circles, arches, or tent arches). The collected data is then prepared for use in the training and testing process of the model. This preparation typically involves several steps, such as pre-processing, image normalization, and data augmentation.
2. The dataset is ready to be fed into the VGG-16 model, which is one of the CNN architectures designed to handle image classification. VGG-16 uses multiple layers of convolution to extract features from fingerprint images, such as line patterns, curves, or circles. This model will process the input data to produce an optimal representation of the feature.

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3. At this stage, the VGG-16 model is trained using a dataset that has been divided into training data. During the training process, the model learns the patterns on the fingerprint by adjusting the weights and biases through an optimization algorithm. This process aims to minimize the prediction error measured through the loss function.
4. After training is complete, the model is tested using a test dataset (test data). This test dataset is typically not used during the training process, so the test results can represent the model's ability to classify fingerprint patterns on new data.
5. After testing, an evaluation stage is carried out to measure the performance of the model. One of the metrics used is accuracy, which is the ratio between the number of correct predictions and the total number of predictions. Accuracy is a key indicator of how well the model recognizes fingerprint patterns.
6. The process ends after the accuracy evaluation is complete. If the accuracy obtained is not optimal, the model can be improved by adjusting parameters, adding additional data, or changing the configuration at the training stage.

III. RESULTS AND DISCUSSION

The fingerprint pattern type image classification using CNN VGG-16 deep learning architecture obtained the following results:

A. Performance Metrics Results of the CNN Model

The performance metrics results of the CNN model use two types of data, namely secondary and primary data, to assess how well the CNN model performs in making predictions. Additionally, previous researchers also compared their results with those of others who applied their methods to the FVC database. Based on these benchmarks, this study achieved the best accuracy.

Table II. Benchmark Results on the FVC Dataset

Researcher's name	Accuracy (%)
Jeon, Wang-Su	97%
P. Nahar	90%
Ramesh Chandra Sahoo	97.5%
Reena Garg	91%
Yucel Cimtay*	98.5%
Diusulkan (VGG-16) lr 0.001	**97.5%**
Diusulkan (VGG-16) lr 0.0001	**100%**

The benchmark results on the FVC dataset show the accuracy levels of various CNN architectures, focusing on the performance of each architecture using the FVC data. The proposed study with the CNN architecture demonstrates competitive results compared to previous research. At a learning rate of 0.001, the VGG-16 architecture yields the most optimal result, comparable to the study by Ramesh Chandra Sahoo with an accuracy of 97.5%. Meanwhile, at a learning rate of 0.0001, the VGG-16 architecture achieved a perfect accuracy of 100%, while the other two architectures had the same accuracy of 97%.

B. Train and Validate Data Sharing Ratio Training Scenarios

Dividing data into data training (training) and data validation (validation) is an important step that greatly affects the accuracy level of the resulting model. Training data is used to train the model to recognize specific patterns in the dataset, while validation data is used to evaluate the model's performance during the training process, without affecting weight updates. In other words, validation data helps detect overfitting, which is a condition where the model is too adaptable to the training data so that its performance degrades on new data.

Table III. Share Data Ratio

Train Ratio : Validation	Accuracy (%)		
	Train	Validation	Testing
60% : 30%	88.25	92.78	93.28
70% : 20%	91.45	97.50	100.00
80%:10%	90.47	97.50	100.00

In the table 3 shows that the data division with a ratio of 70%:20% and 80%:10% results in the best accuracy on the VGG-16 model, with a final accuracy of 100%. The 60%:30% ratio results in lower accuracy than the other two ratios. The training process uses a learning level of 0.0001 with an adam optimizer and 50 epochs.

C. Training Scenarios with Different Epoch Counts

This study tries to apply various scenarios by using different numbers of epochs to train the model, while maintaining the use of Adam's optimizer and a learning rate value of 0.0001. Epoch refers to the number of complete cycles in which the entire training dataset is processed by the model during training. In this scenario, the number of epochs tested is 10, 30, and 50, with the aim of finding the best number of epochs that results in optimal weight in the fingerprint pattern image classification process.

The data sharing ratio used in this study is 80% for railway data, 10% for validation data, and 10% for test data. This ratio is chosen to ensure the model gets enough data for training, while providing sufficient validation data to evaluate the model's performance periodically during the training process. Data testing is used as a final test to assess the model's ability to recognize fingerprint patterns in new data that has never been seen before.

This experiment with different epochs aims to evaluate the influence of epochs on model performance. Too little age can lead to model underfitting, which is a condition in which the model fails to learn important patterns from the data. Conversely, too much age can lead to overfitting, which is a condition in which the model adapts too much to the training data so that its performance degrades on new data.

By using the Adam optimizer, the model is expected to achieve convergence faster and more efficiently. Adam is an optimization algorithm that is widely used in deep learning model training because of its ability to adaptively adjust the learning rate during the training process. The learning level

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used in this study, which is 0.0001, was chosen because this value is often considered a stable conservative option to avoid weight changes that are too large or small in a single update step.

The results of this experiment will be analyzed to determine the best number of epochs that produce optimal accuracy in fingerprint pattern classification. By comparing the performance of the model in each epoch counting scenario, this study is expected to provide insight into the most effective parameter configuration for the VGG-16 model in the context of fingerprint classification. In addition, the study will also evaluate how the number of epochs affects training time, computational efficiency, and the model's ability to generalize new data.

Table IV. Comparison of the Number of Epoch

Epoch	Accuracy (%) 0.0001		
	Train	Validation	Testing
10	55.77	87.50	87.50
30	84.26	97.50	100.00
50	90.47	97.50	100.00

In the table 4, The best results in the table above were obtained using 50 epochs, with the accuracy of train data reaching 90.47%, validation data accuracy of 97.50%, and test data accuracy reaching 100%. This shows that the use of 50 epochs results in the most optimal model for fingerprint pattern image classification with very high accuracy at all stages of evaluation.

D. Training Scenarios with Different Learning Levels

The next experiment was carried out by training the CNN model using the VGG-16 architecture by applying different learning speed variations. The learning rate is an important parameter in the model training process, which determines how much the model's weight changes when making updates based on error gradients. A learning rate that is too small can cause the training process to be very slow, while a learning rate that is too large can cause the model to become unstable or even fail to achieve convergence.

In this scenario, the researcher used the Adam optimizer with a number of epochs of 50 and a data sharing ratio of 80% for the train data and 20% for the validation data. This ratio was chosen to provide a good balance between the amount of data used to train the model and the amount of data used to evaluate the model's performance periodically during training. The use of Adam's optimizer was chosen because of its ability to adjust the learning rate adaptively, so that it can help the model achieve optimal performance more efficiently. This study tested three different learning rate values, namely 0.0001, 0.001, and 0.01. Each value has a unique characteristic in influencing the update of the model's weights during the training process.

The main goal of this experiment is to determine the most optimal learning rate value, which is the value that provides the best balance between stability and convergence speed, and results in the highest accuracy in fingerprint pattern classification. The results of this scenario will be compared based on evaluation metrics such as accuracy, loss, and the model's ability to generalize validation data.

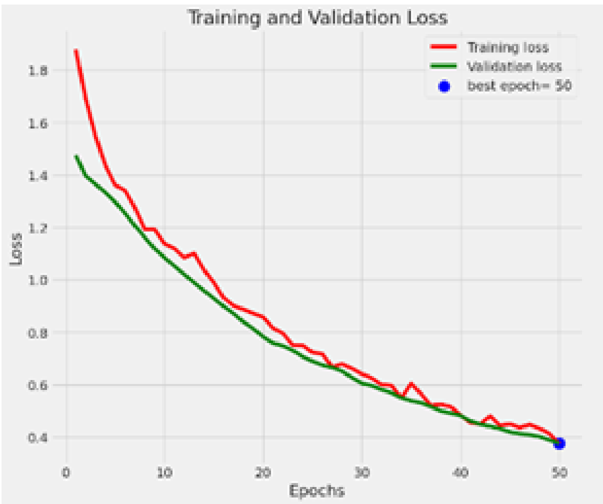
Table V. Comparison of Learning Levels

Learning Level	Accuracy (%)		
	Train	Validation	Testing
0.0001	90.47	97.50	100.00
0.01	87.49	87.50	97.50
0.001	99.69	95.00	97.50

Based on the table 5, experiments using learning rate variations show different accuracy results on the VGG-16 model with Adam optimizer and 50 epochs. At the learning level of 0.0001, the accuracy of the data set reached 90.47%, the validation accuracy was 97.50%, and the testing accuracy reached 100%, which is the best result in the test data. The learning level of 0.01 resulted in lower accuracy, namely 87.49% in train data, 87.50% in validation data, and 97.50% in test data. Meanwhile, the learning level of 0.001 provides the highest accuracy in the data series of 99.69%, with a validation accuracy of 95.00%, and a testing accuracy of 97.50%. From these results, it can be concluded that a learning rate of 0.0001 provides the best accuracy in the test data, while a learning rate of 0.001 indicates the best performance in the training data.

E. Best Results

Of the various experimental scenarios that have been carried out by changing various parameters, the best results are obtained on the CNN model with the VGG-16 architecture. The optimal configuration obtained is by using a data sharing ratio of 80%:10%, Adam optimizer, learning rate 0.0001, and training with 50 epochs. Based on this configuration, we can analyze the accuracy and loss graphs during the training process, as well as review the classification results using the confusion matrix to see the overall performance of the model in the fingerprint pattern image classification.



(a)

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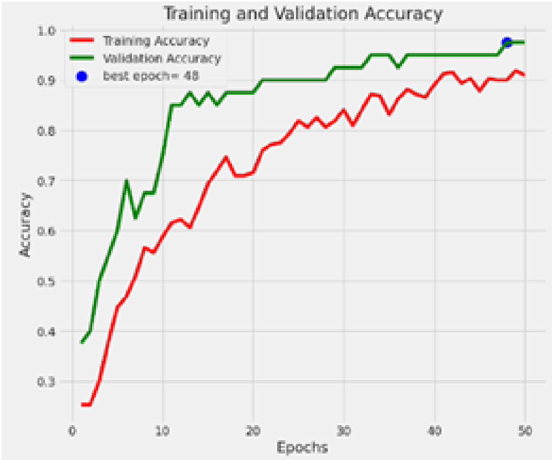

(b)

Fig. 4. A and B are Accuracy and loss charts

Overall, based on image 4 graph shows that the model managed to learn the data very well. This is demonstrated by a consistent decrease in loss value and a steady increase in accuracy during the training process. This pattern reflects that the model is progressively getting better at understanding the relationship between the input and output features of the target. In addition, there is no significant indication of overfitting, as the loss and accuracy lines for training and validation data remain close together during the training process. This consistency shows that the model not only performs well on the training data but is also able to maintain good generalization on the validation data.

The choice of using 50 epochs is based on several considerations. First, it helps prevent overfitting, as training the model for too many epochs could lead it to learn irrelevant details or noise from the data. Second, simpler models like VGG-16 often reach optimal performance with fewer epochs, so 50 epochs may be sufficient. Additionally, training deep learning models requires significant time and computational resources, and 50 epochs offer a balance between training time and achieving good results. Techniques like early stopping can also be used, which halts training once the model reaches its best performance, avoiding unnecessary training. Lastly, previous experiments may have shown that 50 epochs are effective for the given dataset, ensuring the model performs well without excessive training.

This solid result is further reinforced by evaluation using a confusion matrix, as can be seen in the image below. The confusion matrix provides a detailed picture of the model's ability to classify data into the correct classes, thus supporting a more in-depth analysis of the model's performance.

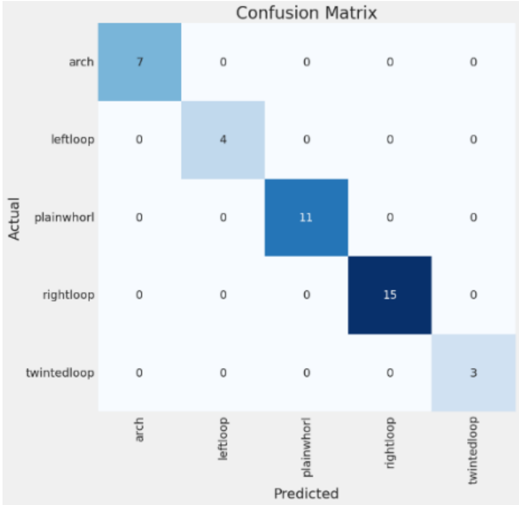

Fig. 5. Confusion matrix data testing

Based on image 5 this confusion matrix, the CNN model used with the VGG-16 architecture shows excellent performance and has a very high degree of accuracy in classifying fingerprint patterns. These results show that the model is able to recognize and group all fingerprint patterns precisely without classification errors, as indicated by the absence of error values in this matrix. With perfect accuracy, this model proves its ability to handle fingerprint data in this regard, making it very suitable for application in fingerprint classification systems. This success also demonstrates the effectiveness of the VGG-16 architecture in understanding the complex features of fingerprint patterns, thus providing confidence for the application of this model to biometric identification systems or similar applications in the future.

IV. CONCLUSION

Based on the results of several training scenarios using Convolutional Neural Network (CNN) with VGG-16 architecture, some interesting conclusions are obtained as follows:

1. The model trained using the VGG-16 architecture successfully classifies all test data with a total of 40 data. These results show that the model has excellent ability to recognize and classify fingerprint patterns into appropriate classes. This success gives an indication that the architecture used is able to capture complex patterns in fingerprint data, resulting in accurate predictions.

2. The best data sharing ratio obtained is 80% for training data, 10% for validation data, and the rest is used for testing. With this sharing, the model is able to learn effectively from the training data which includes most of the available data. The validation data of 10% provides an opportunity for the model to be evaluated periodically during the training process, so as to avoid overfitting. This proportion proved to be a balanced choice between the availability of sufficient training data and representative validation.

3. The highest accuracy was achieved when the model was

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trained with a learning rate of 0.0001 and for 50 epochs. A learning rate of 0.0001 allows the model to update the weights gradually and carefully, thus avoiding the risk of overshooting. In addition, training for 50 epochs provides enough time for the model to learn patterns in the data without taking too long to avoid overfitting. This combination of parameters indicates an optimal balance between the speed of model convergence and generalization capabilities.

4. This fingerprint research can make a significant contribution to researchers or forensic applications. Additionally, the study suggests the use of additional architectures and more data to improve results and accuracy in fingerprint identification.

Overall, the results obtained from this experiment show that the VGG-16 architecture has excellent potential to be applied to fingerprint pattern classification tasks. With the appropriate parameter configuration and the right data sharing ratio, this model is able to show very satisfactory performance.

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