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XCEPTION ARCHITECTURE FOR DEEP LEARNING-BASED FINGERPRINT RECOGNITION Agus Andreansyah 1, Julian Supardi 2* 1,2Departmen of master's in computer science, Universitas Sriwijaya,

Indonesia * Corresponding author : julian@unsri. ac.id ARTICLE INFO ABSTRACT Received : 11 Dec 2024 Accepted : 20 Dec 2024 1

This study proposes a convolutional neural network (CNN) method with an xception architecture model that is used to classify the types of fingerprint image patterns. The data used in this study uses data taken directly using a scanning tool made using FPM 10 A sensors and Arduino Uno. The dataset consists of five types of fingerprint image patterns, namely arch, ulnar loop, whorl, radial loop and twinted loop with a total of 1000 data. The research started from data collection, pre-processing, CNN architecture design, model training and evaluation. The application of the xception architecture shows the best performance with high test accuracy values, stable and consistent. The test scenario of this study is to compare different epoch values, namely 10.30 and 50 and use two learning rates, namely 0.0001 and 0.001. The best test results were obtained at epoch 30 with a learning rate of 0.0001, which was 92% and 93% at epoch 50 with a learning rate of 0.001.

Keywords: Fingerprint; Deep Learning; Convolutional Neural Network; Xception. **1. Introduction** 10

The importance of the role of fingerprint pattern identification as a biometric method is a very important aspect in the process of recognizing a person's identity. The selection of fingerprints as the primary method is based on the unique characteristics of each individual's fingerprint pattern that is physically different and will never be the same as any other individual. This fingerprint pattern has been formed since the fetus is approximately 120 days old in the womb, so each stroke on the fingerprint pattern has its own unique characteristics and formula. The uniqueness and accuracy of fingerprints make them one of the strongest pieces of evidence in various identification processes, including for forensic, security, and administrative purposes. In fact, the fingerprint image pattern has been legally recognized as valid evidence in accordance with Article 184 of the Criminal Code. Therefore, the use of fingerprint recognition technology not only supports effectiveness in identification, but also provides legal certainty in various cases that require accurate identity proof [1], [2], [3], [4]. To obtain fingerprint image patterns, the police usually conduct investigations at the crime scene (crime scene) by collecting evidence in the form of latent fingerprints left behind. However, this identification process often faces various obstacles that make it difficult to collect latent fingerprints optimally. These obstacles are caused by several factors, including: 1. Fingerprints that stick to uneven surfaces, such as wood or other rough textures. 2. Distortion that occurs because the latent fingerprint has been mixed or touched by another person's fingerprint. 3. Latent fingerprints that have been erased due to friction or environmental exposure. 4. Skin surface that has undergone changes, such as wrinkles or damaged skin conditions. These conditions make it difficult to read fingerprint image patterns and require improved image quality so that the identification process can take place better. Therefore, image processing technology plays

an important role in improving the quality of 7

latent fingerprint images so that they can be used optimally. In this study, there are five types of fingerprint image patterns that are used as the basis for analysis. The five types of patterns reflect different unique characteristics and are the focus of the biometric identification process to ensure the accuracy of the results. This effort aims to improve the success of fingerprint identification, especially in cases that require authentic evidence to support legal evidence [5], [6]. Figure 1. Types of Fingerprint Patterns Digital image processing in the forensic world makes a great contribution to improving police efficiency in obtaining evidence in the form of latent fingerprints that are more accurate. This technology also helps reduce errors in system readings, resulting in higher reliability of the identification process. One of the latest approaches used to improve image quality is

artificial intelligence (AI) with **deep learning methods** , such as **Convolutional Neural** Network (**CNN** 5

). CNN is a very effective method for classifying fingerprint image patterns based on the unique characteristics of each pattern. This method is inspired by the way the human brain works in processing information hierarchically. By utilizing large amounts of data (big data), CNN is able to recognize and study complex patterns automatically and with high precision. The way CNNs work begins by retrieving information from input data that has been collected, such as latent fingerprint images. The data is then processed through several layers that have special tasks and functions, such as: 1. Convolutional Layer: Charged with extracting important features from an image, such as a specific line, texture, or pattern. 2. Layer Pooling: Reduces data dimensions without eliminating important information, thereby speeding up the processing process. 3. Activation Layer: Introduces non-linearity to help the model capture complex patterns. 4. Fully Connected Layer: Combines all the features that have been extracted to classify the types of fingerprint image patterns. After going through all these layers, the CNN

will produce an output in the form of 9

a classification of fingerprint pattern types, such as loops, whorls, or arches. With high accuracy, this technology allows the fingerprint identification process to be faster, more efficient, and more reliable. This provides a significant advantage in forensic investigations, especially in cases that require strong and legally valid evidence [7], [8], [9], [10], [11], [12], [13], [14]. The Xception CNN architecture has a significant advantage in high computing efficiency, so it is very suitable for use in image recognition with optimal performance. Xception (Extreme Inception) is a development of the Inception architecture that uses a depthwise separable convolution approach, making it more efficient in terms of calculations without sacrificing accuracy. Feature extraction in this architecture consists of 36 layers of convolution that are designed hierarchically to capture important patterns in imagery more efficiently. Depthwise separable convolution separates the convolution process into two stages: 1. Depthwise Convolution: Captures patterns on each channel independently, reducing the computational load. 2. Pointwise Convolution: Combines information from various channels into a single unit for further analysis. This approach not only speeds up the training and inference process of the model but also reduces the need for computational memory, making it lighter than other traditional architectures. Xception also has high flexibility in handling different types of images, including fingerprint imagery in forensic applications. The combination of computational efficiency and deep feature extraction capabilities makes this architecture superior in classification, segmentation, and detection of image patterns with high precision. Therefore, Xception is an ideal choice for the development of image recognition systems that require high accuracy and efficiency in resource usage. 2. Materials and Methods a. Fingerprint Scanner Design The research began by designing a fingerprint scanner module using the FPM10A sensor. The initial stage that needs to be done is to prepare a PCB board that functions as a link between the sensor and the Arduino Uno. After that, wiring design is carried out to guide the installation of pin cables on the ports that have been provided in each module. The following is the wiring design used. Figure 2. Design Arduino wiring and sensor b. Fingerprint Dataset The total number of fingerprint image pattern data obtained from the scan results is 1,000 data. The data is divided into five types of fingerprint patterns, with each type consisting of 200 data. This division allows the study to analyze the variation of fingerprint patterns in more depth as well as understand the unique characteristics of each type of pattern. Each pattern is labeled according to its type, making it easier to classify and analyze the data. This approach not only improves the accuracy of fingerprint pattern grouping, but also provides a clearer picture of the distribution and uniqueness of each type of pattern. Figure 3. Fingerprint Scan Data This method involves two main stages in processing, namely feature extraction and classification. In the feature extraction stage, this process serves to retrieve important information from the input image, namely fingerprints. The fingerprint image will pass through the first layer, which is the convolutional layer, which is in charge of extracting local features such as lines or curved patterns from the fingerprint image. After that,

the max pooling layer is used to reduce **the** 2

dimension

of the feature while still retaining important information 2

, so that the data size becomes more efficient. In addition, a dropout layer is applied to prevent overfitting by eliminating some random connections during model training. The data is then converted into a one- dimensional form through a flatten layer, which will be further processed on the fully connected layer. The classification stage is in charge of grouping the features that have been extracted into one of several classes of fingerprints. The dense layer or

fully connected layer is used to connect all the neurons of the flattened layer 4

. The output layer is responsible for producing the final result of the classification, where each neuron in this layer represents one of the fingerprint classes. The fingerprint class that is the target of classification consists of five types, namely arch, ulnar loop, radial loop, whorl, and twinned loop. Each class has a unique pattern that is recognized based on its own distinctive characteristics, making the classification process more accurate and structured. Figure 4. Proposed xception architecture Figure 5. Working Process of xception Architecture The Xception architecture is able to process fingerprint image data with a high degree of accuracy thanks to its ability to extract complex features. By utilizing the depthwise separable convolution technique, this architecture not only improves computing efficiency, but also maintains the quality of fingerprint pattern classification. The implementation of this architecture also shows great potential in its application to fingerprint recognition systems in the real world, such as in the fields of forensics, security, and biometric administration. Thus, this research contributes to the development of artificial intelligence-based technology to improve accuracy and efficiency in the fingerprint identification process. 3. Results and discussion This is the result of the implementation of a fingerprint scanner using a 10 FPM sensor and an Arduino Uno. Figure 6. Fingerprint Scanner Thus, the total number of fingerprint data used in this study is 200 data for each type of fingerprint pattern, with a total of 1,000 data. The data will be further analyzed and processed to classify each pattern. The hope is that this process can produce a reliable model that is able to recognize fingerprint patterns with a high level of accuracy. Figure 7. Fingerprint data count bar chart The scenario applied in this study, which uses the Xception architecture on the fingerprint pattern image: a. Comparison Results Using Different Epochs The table below presents a comparison of accuracy values based on the number of epochs of 10, 30, and 50 on primary

data with learning rate settings of 0.0001 and 8

0.001. The results show that an increase in the number of epochs applied tends to improve accuracy in training, validation, and testing data. Table 1. Results of Epoch Comparison Different from Learning Rate b. Accuracy and Loss Graph Results with Learning rate Accuracy and loss graphs have an important role in evaluating, monitoring, and optimizing the performance of CNN models during the training process. Figure 8.

Accuracy and loss graph with learning rate 0.0001 Figure 9. Accuracy and loss graph with learning rate 2

0.001 c. confusion matrix

The following are the results of the confusion matrix from testing 3

100 fingerprint image pattern data. These results describe the performance of the system in classifying various fingerprint patterns using a specific method. Confusion matrix analysis is used to evaluate the accuracy, precision, recall, and error rate of the applied model. Figure 10. Confusion Matrix Primary Data X Architecture Ception 0.0001 Figure 11. Confusion Matrix Primary Data X Ception Architecture 0.001 4. Discussion a. Based on the picture 6, The primary data in this study was obtained using a fingerprint scanner designed by utilizing several main components, such as Arduino Uno, FPM10A type fingerprint sensor, breadboard, and jumper cable. This scanner functions as the main device that supports the course of research, because fingerprint data collected directly is very crucial primary data. The purpose of this data collection is to test hypotheses based on valid and accountable empirical evidence. Thus, the research results obtained become more accurate, reliable, and relevant to the research objectives. b. Based on table 1, The results showed that the use of Xception in fingerprint image processing provided more accurate results than conventional methods. The model training process conducted using labeled fingerprint data with five pattern types (arch, ulnar loop, radial loop, whorl, and twinned loop) showed consistent and effective performance in identifying the unique characteristics of each pattern type. The Epoch score at the learning rate of 0.0001 was obtained the highest score in epoch 30 with the results of training score accuracy of 97.83%, validation of 96% and testing of 92%. Meanwhile, at the learning rate of 0.001, the best epoch value of 50 was obtained with a training score of 96.32%, validation of 95% and testing of 93%. c. The analysis of the results based on Picture 8 The loss graph on the Xception architecture shows a significant decrease in training and validation data as the number of epochs increases. This shows that the model successfully learns to minimize errors during the training process.

At the end of the training, the validation graph appeared stable and 2

showed no indication of overfitting. And then picture 9, In the second graph, the Xception architecture shows a consistent decrease in

training loss (red line) and validation loss (green line 6

) until it reaches stability after several epochs. d. Figure 10, The arch pattern was successfully predicted correctly in 21 samples without any prediction errors. The left loop pattern was correctly predicted in 14 samples, but there was 1 sample that was incorrectly predicted as a plain whorl and 4 samples were predicted as a right loop. Meanwhile, the plain whorl pattern was correctly classified in 16 samples, but the other 2 samples were incorrectly predicted to be twinned loops. This error can occur due to the similarity of the line pattern in the fingerprint image. The right loop pattern was correctly classified in 20 samples, although the other 2 samples were incorrectly predicted as left loops. Finally, the twinned loop pattern was perfectly predicted without any errors in all samples. And then, figure 11, The model managed to correctly predict without error in some classes, thus achieving 100% accuracy. However, for the plain whorl pattern, the model managed to correctly classify as many as 15 data, while the rest still experienced prediction errors, namely 1 data was predicted as a right loop, 2 data as a twinned loop, and 2 data as a left loop. The same thing happened in the right loop pattern, where 1 data was predicted as a plain whorl and 1 other data was predicted as a left loop. From these results, it can be concluded that the model with a learning rate of 0.001 shows quite good performance in classifying fingerprint patterns into five different classes, although there are still some prediction errors in certain patterns. 5. Conclusions Based on the results of several tests by applying several scenarios using the xception architecture, the following conclusions are obtained: 1. Models trained using the Xception-type Convolutional Neural Network (CNN) architecture are able to classify all test data well. These results show that the model can capture complex patterns in the fingerprint imagery, resulting in accurate predictions, despite some incorrectly classified fingerprint patterns. 2. The highest accuracy achieved in the training model with a learning rate of 0.0001 was obtained in the 30th epoch, with the accuracy results for training data of 97.83%, validation data of 96%, and testing data of 92%. Meanwhile, at a learning rate of 0.001, the highest accuracy was achieved in the 50th epoch, with an accuracy value of 96.32% for training data, 95% for validation data, and 93% for test data. References [1] E. Iriyanto and H. Halif, "Elements of Planning in The Crime of Premeditated Murder," Judicial Journal, Vol. 14, No. 1, p. 19, APR. 2021, Yogurt: 10.29123/J.V14I1.402. [2] Triwani, "Dermatogliography Examination as an Identification and Diagnostic Tool". [3] Agus Andreansyah, Rika Favoria Gusa, and Muhammad Jumnahdi, "Fingerprint Pattern Recognition Using MultiClass Support Vector Machine," ELKHA, vol. 11, pp. 79–84, 2019. [4] Didiek Wahju Indarta, "The Function of Fingerprints in the Process of Identifying Victims and Perpetrators at the Bojonegoro Resort Police," 2021. [5] A. Z. Hibatullaha, M. F. Rahmanb, and A. P. Saric, "Utilization of Convolutional Neural Network (CNN) Method with MobileNetV2 Architecture for House Feasibility Assessment," 2024. [Online]. Available: www.elektro.itn.ac.id [6] M. Daktiloskopi, A. Challenge, and D. Harapan, "Human Resource Development Agency for Law And Human Rights of The Ministry of Law And Human Rights of The Republic Of Indonesia 2020 Best Practice Module," 2020. [7] H. Rizkyawan, D. Juardi, J. Haerul Jaman, S. Karawang Jl HSRonggo Waluyo, K. Telukjambe Tim, and K. Karawang, "Forensic Digital Image Analysis of The Authenticity of Image Files Via Whatsapp Using The Nist Method," 2024. [8] C. Militello, L. Rundo, S. Vitabile, and V. Conti, “Fingerprint classification based on deep learning approaches: Experimental findings and comparisons,” Symmetry (Basel), Vol. 13, no. 5, May 2021, yogurt: 10.3390/sim13050750. [9] Rohman Dijaya and Hamzah Setiawan, Digital Image Processing Textbook. UMSIDA PRESS, 2023. [10] M. Hirsi Mohamed, “Fingerprint Classification Using Deep Convolutional Neural Network,” Journal of Electrical and Electronic Engineering, Vol. 9 No. 5 p. 147, 2021, doi: 10.11648/j.j.e.20210905.11. [11] F. Nurona Cahya et al., "SYSTEMASI: Journal of Eye Disease Classification Information System Using Convolutional Neural Network (CNN)," 2021. [Online]. Available: http://sistemasi.ftik.unisi.ac.id [12] M. S. Liyananta, M. Shata, N. Latifah, F. Bimantoro, and T. Informatika, “Program Studi Teknik Informatika,” 2024. [Online]. Available: https://www.kaggle.com/datasets/thomasdubail/brain-tumors-256x256 [13] J. Wira and G. Putra, "Introduction to Machine Learning and Deep Learning Concepts Edition 1.4 (August 17, 2020)," 2020. [14] M. A. Satriawan and W. Widhiarso, "Classification of Facial Recognition to Determine Gender Using Convolutional Neural Network Method," Journal of Algorithms, vol. 4, no. 1, pp. 43–52, 2023, doi: 10.35957/algoritme.xxxx. Application of Xception Architecture for Deep Learning-Based … Vol 22, No 1, 2024 Application of Xception Architecture for Deep Learning-Based … Vol 22, No 1, 2024 Application of Xception Architecture for Deep Learning-Based … Vol 22, No 1, 2024 Application of Xception Architecture for Deep Learning-Based … Vol 22, No 1, 2024 Application of Xception Architecture for Deep Learning-Based … Vol 22, No 1, 2024

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