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Identification of Distorted Fingerprints Using Wavelet Method and Convolutional Neural Network (CNN)

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ABSTRACT

Biometrics offers a valuable tool for disaster victim identification, particularly through fingerprints. However, distorted or damaged fingerprints pose a significant challenge for recognition. This study explores the potential of Wavelet and Convolutional Neural Network (CNN) techniques to enhance the accuracy of distorted fingerprint recognition. Wavelet transform addresses the non-stationary nature of images and reduces detected noise. Convolutional Autoencoder, a CNN component, generates simplified feature representations from input images and attempts to reconstruct them. Utilizing 500 fingerprint samples, the testing results demonstrate accuracy variations ranging from 11% to 59.2%. Image reconstruction achieved 7.16% to 12.47% accuracy, while fingerprint matching attained accuracies between 92.71% and 93.96%. Averaging across all damage levels, the overall accuracy reached 37.65%, with average fingerprint reconstruction at 9.31% and average matching accuracy at 93.03%. The successful reconstruction and matching of distorted fingerprints within a certain range of damage using Wavelet and Convolutional Neural Network highlights the promising potential of these techniques for improved fingerprint identification in forensic and security contexts.

Keywords: Biometric, Distortion, Fingerprint, Wavelet, Convolutional Neural Network.

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INTRODUCTION

Biometrics is a technology for identifying unique characteristics in humans. These unique characteristics include fingerprint patterns, hand geometry, sound frequency keys, iris patterns, and eye retinas which are generally different for each individual. The way biometric technology works is by pattern detection, so it is often used as a security system to maintain the confidentiality of a person's identity data. One biometric technology that is often used in security systems is fingerprint identification [1].

In the field of identification or pattern recognition, digital image processing (image processing) is very helpful for certain parties to interpret images, especially knowing fingerprint pattern recognition, increasing speed and accuracy in identifying fingerprint patterns through human visual means to make it easier to read fingerprint images. finger [2].

Wavelet is a mathematical method that has become a massive alternative in signal or image analysis. In the last few decades, the application of the wavelet transform has been widely used to solve real problems because it can describe non-stationary processes better. When compared to the Fourier transform, the use of wavelets is much more massive and has attracted a lot of attention, especially because of the wavelet's ability to analyze data, both stationary and non-stationary data, and including estimating smooth functions. On the other hand, the shortcomings of the Fourier transform as an analysis tool, especially concerning non-stationary data, include that this method cannot localize the time domain, and the computational complexity of the decomposition algorithm is relatively greater [3].

Convolutional Autoencoder is learning using layers contained in a Convolutional Neural Network (CNN), wherein the learning process, the Convolutional Autoencoder encodes the input image in a set of simple features and then tries to reconstruct the input image. Convolutional Autoencoder has advantages in extracting important features because there is a CNN in the feature learning layer. Besides that, the Convolutional Autoencoder can reduce the dimensions of the input image and reconstruct the features back to the size of the input image [4].

This research aims to explore the potential of Wavelet and Convolutional Neural Network (CNN) techniques to improve the accuracy of distorted fingerprint recognition. It is hoped that these results can help overcome the inaccuracy of distorted fingerprint recognition or even in the case of certain pattern recognition in the scientific field of pattern recognition.

LITERATURE REVIEW

Biometrics

Biometrics is a development of basic identification methods using natural human characteristics as a basis and has played an important role in human identification. Biometrics include physiological characteristics and behavioral characteristics. Physiological characteristics are relatively stable physical characteristics such as fingerprints, hand silhouettes, facial characteristics, tooth patterns, iris patterns, or eye retinas, while behavioral characteristics have a relatively stable physiological basis but are influenced by easily changing psychological conditions such as signatures, speech patterns, or typing rhythm [5].

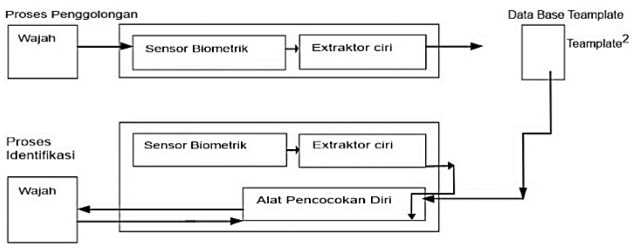

Figure 1. Biometric System Mechanism

The biometric system mechanism can be described with 3 (three) phases:

1) Enrollment phase

In this phase, the input will be scanned (scanned) by a biometric sensor, which is a digital representation of characteristics.

2) Matching phase

In this phase, the database input will be matched with data identification. It is possible to reduce, resulting in a digital representation. These results will be processed with a feature extractor to produce an expressive representation in the form of a template. Depending on the application, the template can be stored in a database in the biometric system or recorded on a magnetic card (smart card).

3) Introduction phase

Individual characteristics are read by a biometric reader (reader). Next, it is converted to digital format, to be processed as a feature extractor (template). The results of this template are then matched with individual identification.

A biometric system is a pattern recognition system to determine or verify a person based on features derived from certain physiological or behavioral characteristics that a person has. Typical physiological or behavioral characteristics, providing basic biometric measurements. Physiological biometrics are based on direct measurements of parts of the human body, such as fingerprints, iris recognition, retina recognition, and facial recognition. Meanwhile, behavioral biometrics are based on measurements and data derived from actions, therefore indirectly measuring the characteristics of the human body, such as signatures, voices, and typing on a computer. Behavioral biometrics usually take longer to verify than physiological biometrics [6].

Biometrics are physiological characteristics and unique traits that each individual has. Biometric systems are used in computer science for identification and access control. In the aspect of human physiology, it can be used as biometric authentication. The biometric system can determine whether the recognition results match or not (known or unknown). Biometric systems have two models, including identification systems and systems [7].

According to the experts above, the author can conclude that biometrics, which is the development of a basic identification method using natural human characteristics as its basis, has had an important role in human identification with physiological biometrics which are based on direct measurements of parts of the human body such as fingerprints, iris recognition, retina, and facial recognition, and is used in computer science for identification and access control, and can be used as biometric authentication in aspects of human physiology.

Fingerprint

Fingerprints are lines or streaks of epidermis found on the skin of a person's fingertips, with a pattern consisting of a series of parallel ridge lines that sometimes cross and end, as well as small features such as terminations and bifurcations that reflect the characteristics of the ridges. locally significant, this pattern can be classified into three main classes, namely Arch, Loop, and Whorl based on the pattern of lines and valleys on its surface. Fingerprint patterns are determined genetically by several genes (polygenic), so no fingerprint pattern is the same between one person and another (individuality). Fingerprints are permanent, they will not change throughout life unless they are changed by chance due to injury, burns, disease, or other unnatural causes (perennial nature and immutability).

The classification of fingerprint parts was first introduced by Galton in 1892. According to Galton, stroke patterns (fingerprints) based on the number of triradii were classified into three forms, namely:

1) Arch (curved line)

The dermatoglyphic pattern is formed by epidermal ridges in the form of parallel lines curved like an arc. This fingerprint shape is the simplest form, it does not have a triradius.

2) Loop (circular line)

The dermatoglyphic pattern is a flow of parallel lines that rotate 180°. The pattern area in the loop is surrounded by radiants or type lines. The pattern consists of a series of strokes that run parallel to enter the pattern area, then turn 180º and leave the pattern area on the same side as the strokes entered. The core of the loop is in the form of a straight line like a stalk or a collection of two or more lines that run parallel and are traversed by other lines that curve above it. The loop has a triradius on the distal lateral part of the phalanx.

3) Whorl (vortex)

The dermatoglyphic pattern is formed by twisted lines of the epidermal ridges in the form of swirls. The patent area on the whorl is the same as a loop surrounded by radiants or type lines. The pattern consists of a series of strokes that encircle the core. The core of the whorl is in the form of a point or short stroke and has two or more triradii. One triradius is located on the radial/tibial side and the other is located on the ulnar/fibular side of the pattern.

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Figure 2. Fingerprint Characteristics

Fingerprints are the most widely used biometric characteristic for personal identification. One of the primary responsibilities of the integrated automated fingerprint identification service (IAFIS) of the most well-known law enforcement organizations is fingerprint identification. Fingerprint patterns are defined by a series of parallel ridge lines that sometimes cross and terminate. Small features reflect the two most significant local ridge characteristics: termination and bifurcation. Ridge termination is described as the abrupt end of a ridge, while ridge bifurcation is the point where a ridge splits into branch ridges. The uniqueness of a fingerprint is determined by the quality and connections of its local ridges. The majority of fingerprint comparison techniques rely on minutiae matching [8].

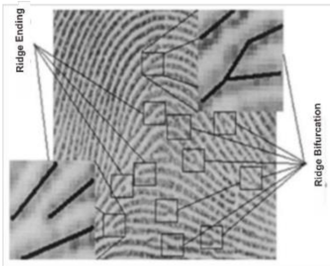

Figure 3. Ridge Edges and Bifurcations

Fingerprints are a pattern of lines (ridges) on the surface of a fingertip. Based on the pattern of lines (ridges) and valleys (valleys), fingerprints can be classified into three main classes, namely: Arch, Loop, and Whorl (E. Henry, 1901). According to Galton, about 60% of fingerprints are loop type, 30% are whorl type, and 10% are arch type. To identify a person's fingerprints, what must be found are the characteristics of the fingerprint. These characteristics can be found if the structure can be understood [9].

Fingerprint distortion is classified into five types, including dry, dirty, oily, rotational, and partially cut off as shown in Figure [10].

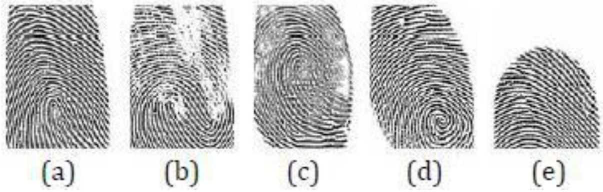

Figure 4. Ridge Edges and Bifurcations

1) Fingerprints (a) are normal fingerprints, fingerprint patterns that usually form naturally in each individual. Consists of circle and cross patterns. This pattern is the most common and is the basis for fingerprint classification systems.
2) Fingerprints (b) are dirty fingerprints, fingerprints that are formed when the fingers or skin of the hand are exposed to dirt or other substances such as oil, soil, dust, or other liquids. This condition can make fingerprint reading less clear or even change the fingerprint pattern temporarily.
3) Fingerprints (c) are oily fingerprints that occur when the skin of the hands produces natural oils that can leave traces when touching a surface. This oil can affect the quality of fingerprints because there is a layer of oil between the skin and the surface which makes fingerprints difficult to read clearly.

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4) Fingerprints (d) are circular or rotating fingerprint patterns. This pattern may be more difficult to identify because the main features of the fingerprint pattern cannot be recognized due to the unusual twisting or curving.
5) Fingerprints (e) are partial fingerprints that occur when not the entire surface of the finger touches the media used to take fingerprints. This can happen for various reasons, for example when a person only touches the surface with a small part of the finger or when the finger is injured so that only part of the fingerprint pattern remains.

Wavelet

According to Percival, wavelet is a name for small waves that rise and fall over certain periods. Wavelets are divided into two types, namely father wavelet (ϕ) and mother wavelet (ψ) which have the properties: $\int_{-\infty}^{\infty} \phi(t)dt = 1$ dan $\int_{-\infty}^{\infty} \psi(t)dt = 0$. If the gender is not mentioned, the word wavelet refers to the mother's wavelet. The father wavelet is sometimes also called the scale function. Wavelets have offspring, namely translation and dilation forms of the father wavelet and mother wavelet, namely [11]:

$$\phi_{j,k}(t) = (2^j)^{\frac{1}{2}}\phi(2^j t - k) \quad (1)$$

$$\psi_{j,k}(t) = (2^j)^{\frac{1}{2}}\psi(2^j t - k) \quad (2)$$

According to Olkkonen, the wavelet transform is an improvement on the Fourier transform. The Fourier transform can only determine the frequency that appears in a signal but cannot determine when (where) that frequency appears. If the signal, scaling function, and wavelet are discrete, then the wavelet series equation or discrete signal is called DWT (Discrete Wavelet Transform). The DWT over a sequence contains two series expansions, one for sequence approximation and the other for sequence details. The formal definition of DWT over an N-point series $x[n]$, $0 \le n \le N - 1$ [12] is given by:

$$DWT\{f(t)\} = W_\phi(j_0, k) + W_\psi(j, k) \quad (3)$$

Where

$$W_\phi(j_o, k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x[n]\phi_{j_0 k}[n] \quad (4)$$

$$W_\psi(j, k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x[n]\, \psi_{j,k}[n] \;\; j \ge j_0 \quad (5)$$

The series $x[n]$, $0 \le n \le N - 1$ can be recovered from the DWT coefficients $W\phi$and $W\psi$, which are given by:

$$x[n] = \frac{1}{\sqrt{N}} \sum_k W_\phi(j, k)\, \phi_{j_0 k}[n] + \frac{1}{\sqrt{N}} \sum_{j=j_0}^{\infty} \sum_k W_\psi(j, k)\, \psi_{j_0,k}[n] \quad (6)$$

Wavelet transform is a conversion function that can be used to divide a function or signal into different frequency components, which can then be studied according to their scale. Wavelet decomposition is a technique for decomposing signals into detailed coefficients and approximation coefficients using HPF, LPF, and downsampling. The decomposition process is part of signal analysis with DWT and reconstruction is part of signal synthesis with multilevel back DWT up to a certain octave. Discrete wavelet transform can be used in the initial signal processing to obtain information about the characteristics of the signal. The level of decomposition affects the level of network recognition, namely the higher the level of decomposition, the lower the level of network recognition [13].

Wavelet is almost close to the Fourier transformation, if Fourier only allows placement in a function of time, Wavelet allows placement of time in different frequency components. Wavelet transformation itself is divided into two, namely continuous and discrete, which are derived from the mother wavelet through decomposition shifting and scaling. Therefore, the resulting transformation characteristics depend on the mother wavelet itself [14].

Convolutional Neural Network

A convolutional neural network is a neural network model. Like neural network models in general, the CNN model has a fully connected network structure, namely layers of neurons that are interconnected with the neurons of the previous layer. The CNN architecture has capabilities that ordinary neural networks do not have, namely the ability to capture contextual information contained in data such as pixels that are close to each other in an image or words that are close to each other in text. Apart from that, the CNN model has lower complexity, faster model training time, and requires fewer training data samples than ordinary neural network models.

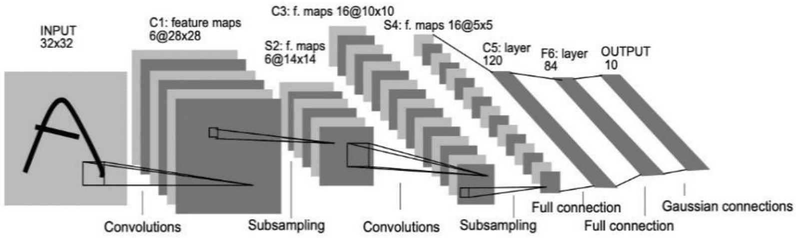

Figure 5. LeNet5 Model Architecture

The LeNet5 model proposed by LeCun is perhaps the first CNN model that utilizes structural information in data through a convolutional and pooling operation in the neural network layer (see Figure 5). The success of the LeNet5 model in image data classification problems has encouraged the development of more complex deep learning models to handle various image data analyses.

The CNN model consists of several layers as follows:

1) Input layer: The layer that functions to generate input data.
2) Convolutional layer: This layer functions for convolution operations on several nodes using several filters.
3) ReLU Layer: This layer is the activation function of the previous layer's output.
4) Pooling layer: This layer functions to sample the output of the previous layer to produce a structure with smaller dimensions.
5) Fully connected layer: This layer functions to calculate the output from the last layer of the neural network model.

Convolution Operations

The convolution operation on images is a pixel-based filtering operation using a filter on all parts of the image. The convolution output obtained by shifting a filter in the horizontal and vertical directions contains the number of times the filter element is multiplied by the pixel value at the corresponding position of the image. The convolution operation can be formulated as follows. If we are given an image that is presented as a 2-dimensional pixel matrix a[i,j] of size M x N where I =0,1,.., M

– 1 is the row index and j = 0,1,.., N – 1 is the column index; and h[I,j] is a filter (kernel) of size m x n and it is assumed that all filter elements outside the matrix of size m x n have a value of 0 then the convolution operation is defined as:

$$a \ast h = \sum i=0,1,..,m-1 \sum j=0,1,..,N \; h(i,j)a(m - i,n - j) \quad (7)$$

The convolution operation can be seen as a process of filtering all parts of the image by moving a filter in the horizontal and vertical directions of the image (see Figure 6). Apart from the filter size, other parameters of the convolution operation are stride and padding.

The stride parameter is a parameter that determines how many pixels the filter will shift in the horizontal and vertical directions. If the stride value is 1, then the filter will shift by 1 pixel horizontally and vertically. In Figure 6, the stride value used is 1, and in Figure 7, the stride value used is 2. Thus, the smaller the stride used, the more detailed the convolution result information will

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be or the smaller the resolution of the resulting feature map. However, the smaller the stride, the higher the computational load that the computer must carry out.

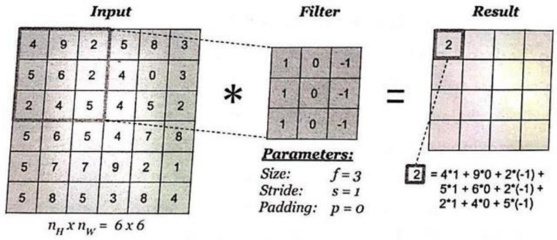

Figure 6. Image Convolution Operations Use a Filter

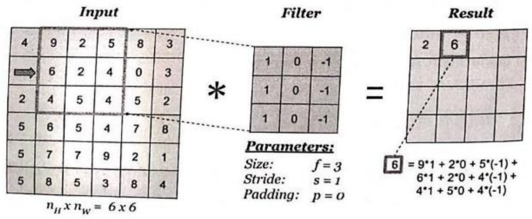

Figure 7. Influence of Stride (S=1) on Convolution

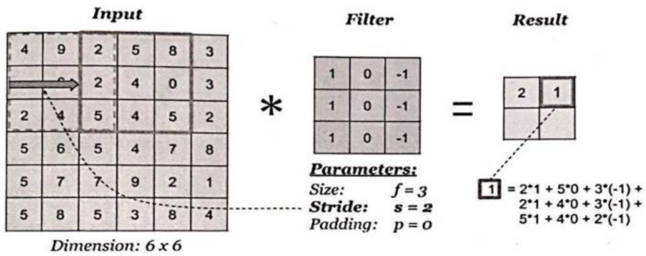

Figure 8. Influence of Stride (s = 2) on Convolution

The padding parameter determines the number of pixels containing the value 0 that are added to each side of the input image before the convolution operation is carried out.

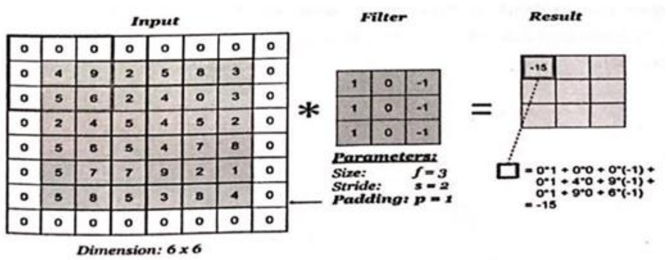

Figure 9. Influence of Padding (p = 1) on Convolution

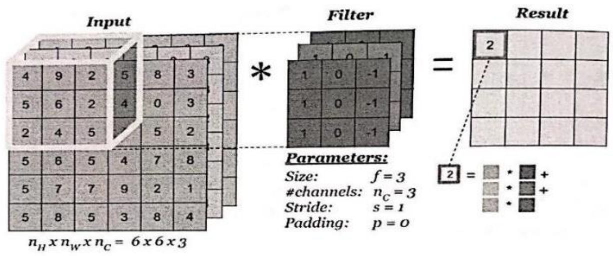

Figure 10. Influence of padding (p = 0) on Convolution

Pooling Operations

Pooling is selecting a pixel value representing several neighboring pixel values in a feature map and ignoring other pixel values. Two pooling operators that are often used are max pooling and average pooling.

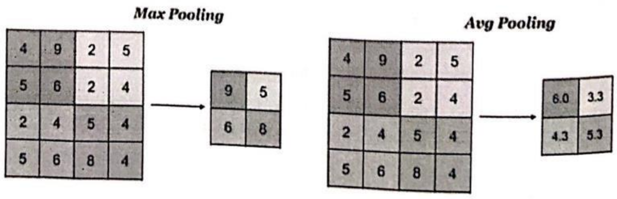

Figure 11. Max Pooling and Average Pooling

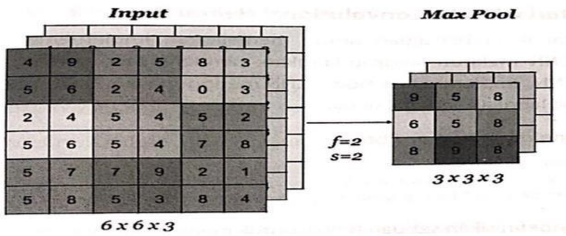

Figure 12. Max Pooling on 3-dimensional Data

Unpooling Operation

Unpooling is the opposite of pooling where the pooling result value (maximum value) is returned to its original position in the feature map and the other pixel values are filled with a value of 0.

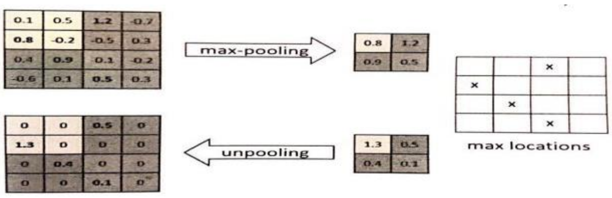

Figure 13. Max Pooling of 3-dimensional Data

According to LeCun, convolutional neural networks, also known as convnets, are a method for processing data in the form of several arrays, such as a color image consisting of three 2D arrays containing pixel intensity in three types of colors. Experts currently claim that convolutional neural networks (CNN), a more specialized application of artificial neural networks (ANN), are the best model for solving technical object recognition problems. The architecture of convolutional neural networks is trainable and comprises several stages. The input and output of each stage are several arrays called feature maps.

Abhirawa states that a convolutional neural network (CNN) evolves from the multi-layer perceptron (MLP) method, specifically designed to process two-dimensional data. Artificial neural network (ANN) modeling fundamentally relies on the CNN concept for image or video recognition. The deep neural network type includes CNN due to its high and structured network model depth level, which it frequently applies to image data both directly (in real-time) and indirectly.

According to Divineyah, a convolutional neural network (CNN) is a development of the multilayer perceptron (MLP), which is specifically designed to process two-dimensional data, especially image data. CNN, a type of deep neural network, boasts a greater network depth than MLP. CNN finds widespread application in image data due to its ability to store spatial information, thereby yielding superior results compared to MLP. MLP is not suitable for use in image classification cases because it considers each pixel as an independent feature without considering the spatial information in the image data.

The author can conclude that a convolutional neural network (CNN) is a neural network model with a fully connected network structure, specifically designed for processing two-dimensional data, according to the experts mentioned above. It is currently the most effective model for solving object recognition problems using artificial neural networks (ANN).

METHODOLOGY

We use the wavelet and convolutional neural network (CNN) methods to recognize distorted fingerprint patterns with a certain level of damage. We use Wavelet for image restoration and CNN for identification. The research began with the collection of fingerprint image data sets. We obtained the dataset for this study from the Indonesian National Police. The sample The sample data, which included the right thumb, left index finger, left middle finger, left sweet finger, left and right fingers, and left little finger, amounted to 500 data points. The recognition process begins with training on the existing dataset. The recognition process continues with noise reduction using wavelets, reconstruction using CNN Autoencoder, and matching using CNN. We implemented this research using the Python 3.1.1 programming language.

RESULTS AND DISCUSSION

Implementation begins with wavelets for noise reduction, followed by a convolutional neural network (CNN) for fingerprint image reconstruction, and a CNN for fingerprint matching. This study defines the degree of fingerprint damage as the level of imperfection or information loss in an individual's fingerprint. The development of distorted fingerprint identification refers to the extent of a damaged fingerprint's recognition capacity. The results of the research are described in the following.

Figure 14. Distorted Fingerprint Recognition UI

Figure 14 shows the interface used to implement the combination of wavelets and CNN. To import the modules used, below is an example of the program code.

```
import cv2
import numpy as np
import os
from PIL import Image
from matplotlib import pyplot as plt
from keras.models import load_model
from sklearn.metrics.pairwise import cosine_similarity
from PIL import Image
import tensorflow
from tensorflow.keras.preprocessing import image
import pywt
```

Figure 15. Program Code 01. Import the Modules Used

Before being used for identification, training must be carried out to be able to read accurately. The following program code 02 is used to load the dataset from the storage directory, the dataset is used to train and test the autoencoder model. Image data will be resized to 512 x 512 and converted to grayscale.

```
train_data_dir = 'datset3/train'
test_data_dir = 'datset3/test'
train_datagen = ImageDataGenerator(rescale=1.0/255.0)
test_datagen = ImageDataGenerator(rescale=1.0/255.0)
batch_size = 32
train_generator = train_datagen.flow_from_directory(
train_data_dir, target_size=(512, 512),batch_size=batch_size,
class_mode='input', color_mode='grayscale')
test_generator = test_datagen.flow_from_directory(
test_data_dir, target_size=(512, 512),
batch_size=batch_size,
class_mode='input', color_mode='grayscale')
```

Figure 16. Program Code 02. Training

```
def preprosess_gambar(path_file):
image = Image.open(path_file).convert('L')
resized_image = image.resize((512, 512))

coeffs = pywt.dwt2(resized_image, 'db8')
cA, (cH, cV, cD) = coeffs

threshold = np.std(cD) * 5
print(threshold)
cD_thresh = pywt.threshold(cD, threshold, mode = hard')

coeffs_filt = cA, (cH, cV, cD_thresh)
image_denoised = pywt.idwt2(coeffs_filt, 'db8')
new_fingerprint_data = np.array(image_denoised) / 255.0
new_fingerprint_data =
new_fingerprint_data.reshape(1,512, 512, 1)
return new_fingerprint_data
```

Figure 17. Program Code 03. Wavelet Denoising

Program code 03 above is used for preprocessing fingerprint image data and denoising using wavelets, the image will be resized to 512x512 and converted to a grayscale then transformed using Wavelet Daubechies 8 for noise reduction.

```
def reconstruct(filename, gambar_preproses):
model_rekonstruksi = load_model('D:/Biometric/Res/
autoencoder_fingerprint.h5')
hasil_rekonstruksi =
model_rekonstruksi.predict(gambar_preproses)
nama_file = 'reconstruct' + str(filename)
path_hasil_rekonstuksi = 'D:/Biometric/Res/
static/' + nama_file
plt.imsave(path_hasil_rekonstuksi,
hasil_rekonstruksi.reshape(512, 512), cmap = 'gray')
print(nama_file)
return nama_file
```

Figure 18. Program code 04. Fingerprint Reconstruction

Program code 04 above is used to reconstruct fingerprint images. The CNN model that has been trained in the previous stage will be reloaded in h5 format. Then the reconstruction results will be saved in the specified storage or computer directory.

```
def matching_gambar_sidikjari_methode2(file_path):
model = load_model('D:/Skripsi-ruslan/Skripsi-
ruslan/match1_model.h5', compile=False)
storage_directory =
'D:/Biometric/Res/static/match_data'
storage_images = []
storage_features = []

```

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```
for filename in os.listdir(storage_directory):
if filename.endswith(".jpg"):
img_path = os.path.join(storage_directory, filename)
img = image.load_img(img_path, target_size=(512, 512))
img_array = image.img_to_array(img)
img_array /= 255.0

feature_vector =
model.predict(np.expand_dims(img_array,
axis=0))[0]

storage_images.append((img_path, filename))
storage_features.append(feature_vector)
```

Figure 19. Program Code 05. Fingerprint Matching

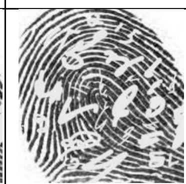
Program code 05 above is used to match fingerprint images. The CNN model that has been trained in the previous stage will be reloaded in H5 format. Next, we will match the reconstruction results with the fingerprint image data in the match data directory. The fingerprint image matching results manifest as similarities or fingerprint patterns that align with the newly acquired fingerprint image data. Following are the results of denoising, reconstruction, and matching.

Figure 20. Denoising, Reconstruction and Matching

Testing

At this stage, testing was carried out to see whether the Wavelet and Convolutional Neural Network (CNN) methods could identify distorted fingerprints. Testing for the level of fingerprint damage and fingerprint matching will be explained in the table below. Testing for distorted fingerprints uses 4 fingerprint data and each fingerprint data is tested with a gradual level of damage.

Table 1. Distorted Fingerprints

Basroh					
Normal	**Distortion %**				
	37	38	39	38,6	38,9
					
	39,8	39,9	40	41	42
					

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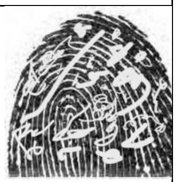
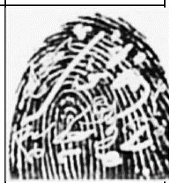
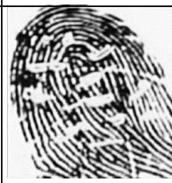
Rani					
Normal	**Distortion %**				
	57	58	59	59,1	59,2
					
	59,3	59,4	60	61	62
					
Aldy					
Normal	**Distortion %**				
	11	12	13	13,6	13,7
					
	13,8	13,9	14	15	16
					
Nunung					
Normal	**Distortion %**				
	35	36	37	37,8	37,9
					
	38	38,1	38,2	39	40
					

Table 2. Fingerprint Reconstruction

Basroh					
Normal	**Reconstruction %**				
	10,40	10,40	10,40	10,40	10,40
					
	10,46	10,46	10,46	10,46	10,46
					
Rani					
Normal	**Reconstruction %**				
	12,42	12,42	12,42	12,42	12,42
					
	12,33	12,33	12,33	12,33	12,33
					
Aldy					
Normal	**Reconstruction %**				
	7,18	7,18	7,18	7,18	7,18
					
	7,16	7,15	7,16	7,15	7,16
					
Nunung					
Normal	**Reconstruction %**				

	7,31	7,31	7,31	7,31	7,31
					

Table 3. Basroh Fingerprint Testing

Fingerprint Data	Fingerprint Damage %	Fingerprint Reconstruction %	Fingerprint Matching %
Basroh	37	10,4	93,2
	38	10,4	93,09
	39	10,37	93,01
	39,6	10,42	92,96
	39,7	10,42	92,93
	39,8	10,46	Not detected
	39,9	10,46	Not detected
	40	10,46	Not detected
	41	10,46	Not detected
	42	10,46	Not detected

Based on the Basroh test table, the average fingerprint repair results reached 10.40% and the limit for the level of fingerprint damage that could be matched reached 39.7% and obtained an average matching accuracy of 93.03%.

Table 4. Rani Fingerprint Testing

Fingerprint Data	Fingerprint Damage %	Fingerprint Reconstruction %	Fingerprint Matching %
Rani	57	12,42	93,18
	58	12,43	93,14
	59	12,47	93,07
	59,1	12,35	92,97
	59,2	12,35	92,81
	59,3	12,33	Not detected
	59,4	12,34	Not detected
	60	12,32	Not detected
	61	12,32	Not detected
	62	12,32	Not detected

Based on Rani's test table, the average fingerprint repair results reached 12.40% and the limit for the level of fingerprint damage that could be matched reached 59.2% and obtained an average matching accuracy of 93.03%.

Table 5. Aldy Fingerprint Testing

Fingerprint Data	Fingerprint Damage %	Fingerprint Reconstruction %	Fingerprint Matching %
Aldy	11	7,18	93,96

	12	7,17	93,80
	13	7,16	93,77
	13,6	7,16	93,74
	13,7	7,16	93,70
	13,8	7,16	Not detected
	13,9	7,15	Not detected
	14	7,16	Not detected
	15	7,15	Not detected
	16	7,16	Not detected

Based on the Aldy test table, the average fingerprint repair results reached 7.16% and the limit for the level of fingerprint damage that could be matched reached 13.7% and obtained an average matching accuracy of 93.79%.

Table 6. Nunung Fingerprint Testing

Fingerprint Data	Fingerprint Damage %	Fingerprint Reconstruction %	Fingerprint Matching %
Nunung	35	7,31	92,99
	36	7,35	92,91
	37	7,34	92,78
	37,8	7,34	92,73
	37,9	7,33	92,71
	38	7,33	Not detected
	38,1	7,33	Not detected
	38,2	7,34	Not detected
	39	7,33	Not detected
	40	735	Not detected

Based on the Nunung test table, the average fingerprint repair results reached 7.33% and the limit for the level of fingerprint damage that could be matched reached 37.9% and obtained an average matching accuracy of 92.82%.

Test result

Based on the test results of the four fingerprint data, the identification of distorted fingerprints using the Wavelet and Convolutional Neural Network methods can reduce noise, reconstruction, and matching. Based on Table 2, the highest, lowest accuracy and average results of the entire test can be seen as follows:

1) The lowest accuracy obtained from the damage level testing results reached 11%, reconstruction reached 7.16% and matching reached 92.71%.
2) The highest accuracy obtained from the damage level testing results reached 59.2%, reconstruction reached 12.47 and matching reached 93.96%.
3) The average result of the overall damage level test reached 37.65% the average reconstructed fingerprint reached 9.31% and the average accuracy for matching reached 93.03%.

CONCLUSION

Based on the results and discussion, it can be concluded that the use of the Wavelet and Convolutional Neural Network methods provides quite good results in reconstructing and matching distorted fingerprints with a certain level of damage. Therefore, Wavelet and Convolutional Neural Network methods can be used effectively for the reconstruction and matching of distorted fingerprints, although the results may vary depending on the degree of damage and the quality of the fingerprint images used.

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