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Comparative Analysis between Generalized Hough Transform and Neural Networks in Fingerprint Recognition

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Abstract

This in-depth study aims to evaluate and compare the performance of two major methods in the field of fingerprint recognition: the generalized Hough transform and Siamese neural networks. To do this, we carried out an exhaustive comparison on a representative sample of 628 fingerprints for each of the models, using the CASIA database, recognised for its diversity and appropriate size for accurate evaluations.

The Siamese neural networks stood out by displaying remarkable accuracy, exceeding 99.2%. Their ability to process large datasets efficiently underlines their relevance in biometric scenarios requiring in-depth analysis. In contrast, the Generalized Hough Transform achieved a respectable accuracy rate of 97.7%, confirming its reliability even in more limited data contexts.

This analysis highlights the distinct advantages of each approach, with particular emphasis on the adaptability of Siamese neural networks to complex variations in fingerprints. Their ability to generalise models to large datasets demonstrates their robustness and potential for large-scale biometric applications.

To evaluate this performance, we used measures such as the confusion matrix, which provides a clear visualisation of the relationship between predicted and actual values, and the F1 score, which provides a balanced assessment of precision and recall.

The results discussed enrich our understanding of the issues involved in biometric security and open up promising prospects for future research in this constantly evolving field.

Keywords

Hough Transform; confusion matrix; F1-score

I INTRODUCTION

Fingerprint recognition remains an essential pillar of biometric systems, playing a vital role in the identification and authentication of individuals, with diverse applications ranging from securing mobile devices to physical access control systems and forensics.

Faced with this growing importance, the scientific community is exploring various approaches aimed at improving the accuracy and efficiency of fingerprint recognition systems. These approaches include both traditional methods based on geometric features, such as the Hough

transform, and modern approaches exploiting advances in deep learning, such as convolutional neural networks (CNNs) [12][6] .

In this context, our study aims to carry out a comprehensive performance evaluation of two distinct approaches to fingerprint recognition: the generalized Hough transform and the neural network method, more specifically Siamese neural networks. Siamese neural networks are a particular variant of neural networks used to compare pairs of inputs [7]. We have chosen the CASIA database, renowned for its diversity and size, as our testing ground.

Our aim is to compare the ability of these two methods to deal with complex variations in fingerprints, to provide accurate results and to adapt to realistic operational conditions. This evaluation goes beyond the simple measurement of accuracy and includes an in-depth analysis of the advantages and limitations of each method, providing crucial information for the design and deployment of reliable biometric systems.

To assess the performance of each method, we use key evaluation metrics, including the confusion matrix, which visualises the correspondence between the values predicted by the model and the actual values, and the F1 score, which provides a balanced measure of precision and recall by taking into account both false positives and false negatives.

This in-depth study, which combines the analysis of traditional and modern measures, aims to provide a holistic understanding of the comparative performance of the generalised Hough transform and the neural network method in the field of fingerprint recognition. The results obtained will be crucial in guiding the design and implementation of robust and reliable biometric systems.

II METHOD DESCRIPTION

2.1 The database

The choice of database is of crucial importance in our study, as it is the essential testing ground for evaluating the performance of fingerprint recognition methods. We opted for the CASIA database, renowned for its reputation, substantial size and carefully organised diversity.

The CASIA database is large, comprising an extensive collection of fingerprints from a variety of sources. It is organised into 500 files numbered from "000" to "499", each representing a specific individual. Each subject is associated with two distinct sub-folders, 'L' (left) and 'R' (right), each containing 20 fingerprint images [14]. This is illustrated in the figure below.

This database contains a total of 20,000 fingerprint images, covering a wide variety of conditions, people and environments. The large size of the CASIA database plays a crucial role in obtaining robust and generalisable results, which are essential for evaluating the performance of fingerprint recognition methods in various scenarios. The diversity within the CASIA database is of paramount importance, as it accurately reflects the real conditions that fingerprint recognition systems face. Fingerprints come from a diverse range of individuals, including natural variations such as age, gender and ethnicity. In addition, the database captures different finger positions, varying levels of illumination and other environmental factors that contribute to its rich diversity [13].

In opting for the CASIA database, our aim is to ensure a comprehensive and representative evaluation of the performance of fingerprint recognition methods. This selection takes into

account the complexity of real-world conditions, thus providing a solid basis for relevant and applicable conclusions.

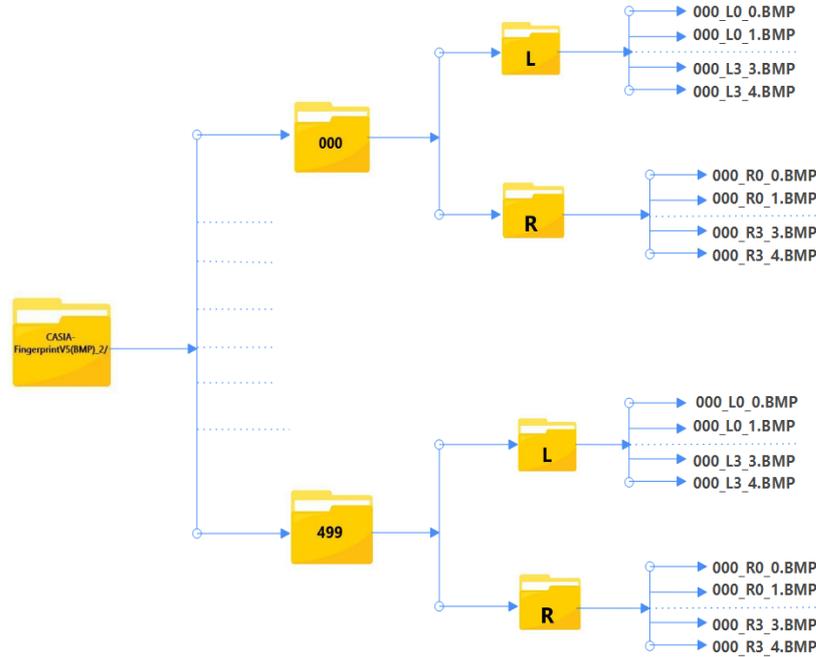


Figure 1: Structure of the CASIA-FingerprintV5(BMP)_2 database.

2.2 Hough Transform

The generalised Hough transform occupies a crucial position in the field of fingerprint recognition, playing the essential role of detecting and extracting specific features, such as minutiae, from an image. This method is based on the fundamental principle of the Hough transform, originally developed for detecting lines in images, and its generalised version extends this concept to detect more complex shapes, such as curves and circles, making it particularly suitable for fingerprint analysis [4].

In this section, we detail the implementation of the generalised Hough transform, highlighting the link between its generality and our study. We begin by describing the data pre-processing, during which fingerprint images are subjected to various techniques, such as intensity normalisation, segmentation and binarisation, in order to remove noise. The Zhang-Suen algorithm is then used to reduce the thickness of the minutiae to the size of a pixel, making them easier to extract.

a) Data preprocessing

The impression images were subjected to various pre-processing techniques [1][8], such as intensity normalization, segmentation, and binarization, to eliminate noise. Then, the Zhang-Suen algorithm [3] was applied to each block to reduce the thickness of the minutiae to the size of a pixel, thus facilitating their extraction.

Here is an overview of the various stages of fingerprint image preprocessing.

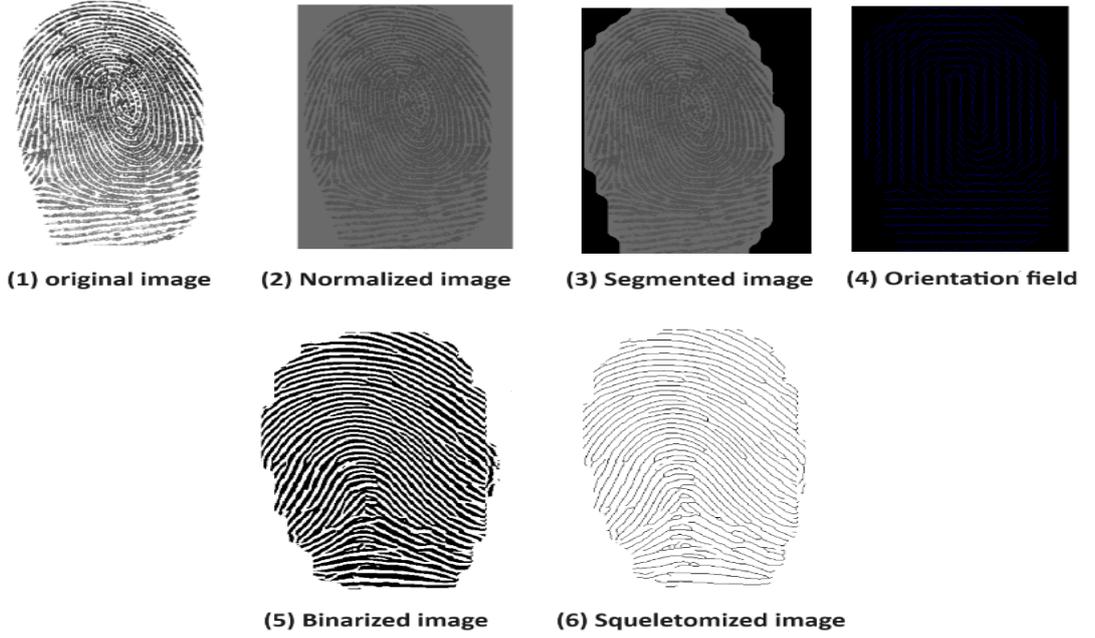


Figure 2: Stages of fingerprint image preprocessing.

b) Minutiae extraction

The minutiae are unique characteristics of the fingerprint that allow for its identification and verification [2]. Each minutia m_i is represented by a quadruplet of coordinates: $m_i = (x_i, y_i, \theta_i, t_i)$ [10]. The coordinates x_i and y_i correspond to the position of the minutia in the image, θ_i represents its direction, which is generally calculated from the local orientation of the ridge, and t_i indicates whether the minutia is a termination or a bifurcation type. Bifurcations and terminations are key points for comparing fingerprints.

For each black pixel in each block of the fingerprint, we calculate the Crossing Number (CN) indicator [2], which is a measure of local topology. The formula for the CN indicator is as follows:

$$CN = \frac{1}{2} \sum_{i=1}^8 |p_i - p_{i+1}| \quad (1)$$

$$\text{with } p_9 = p_1$$

The neighboring pixels p_1, \dots, p_9 are arranged in a clockwise order. Using the properties of the CN, as summarized in the table above, each ridge pixel can be classified as either a termination, a bifurcation, or a point without a minutia. Specifically, an isolated pixel will have a CN of 0, a termination will have a CN of 1, a continuous ridge will have a CN of 2, a bifurcation will have a CN of 3, and a crossing will have a CN of 4 [2]. This information is essential for minutiae extraction and fingerprint comparison.

c) Calculation of minutiae orientation

To determine the orientation of a minutia m , we seek to find the line that passes through m and that best fits the surrounding connected points. We use a simple linear regression method [13] for this purpose. By then applying the $atan$ function to the slope of the line, we obtain the orientation of the minutia.

d) Comparison of minutiae

After the pre-processing phase of the fingerprint image, we use an adapted Hough transform algorithm, followed by a matching algorithm to detect and connect the corresponding feature points. The adapted Hough transform algorithm uses mathematical equations in a parameter space to determine the spatial relationships between the feature points. These parameters describe the characteristics of the spatial relationships, such as the distance and angle between the minutiae .

The algorithms for the adapted Hough transform and the matching are illustrated below, respectively:

Algorithm II.1 : Generalized Hough Transform Algorithm

```
1 Input: Two sets of minutiae
2 Output: The parameter transformation
3 minutia as M in algorithm
4 Start by initializing an accumulation matrix.
5 For each M in the first set :
6   For each M in the second set :
7     Calculate the angle difference between the two minutiae :
8     angle_diff = min (|| angle_M_1 - angle_M_2 ||, 360 - || angle_M_1 - angle_M_2 ||)
9     angle_diff = 360_degree - angle_diff
10    position_diff_x = x_M_1 - (x_M_2 * cos(angle_diff) - y_M_2 * sin( angle_diff ))
11    position_diff_y = y_M_1 - (x_M_2 * sin(angle_diff) + y_M_2 * cos(angle_diff ))
12    accumulation_matrix[ position_diff_x ][ position_diff_y ] += 1
13 return the peak position in the accumulation matrix.
```

Algorithm II.2 : Matching of two sets of minutiae

```
1 Input: Two sets of minutiae
2 Output: List of paired minutiae
3 Minutia as M in algorithm threshold as th
4 Initialization of the list and the counter count
5 For each M in the first set :
6   For each M in the second set :
7     If position_diff_x < th1 and position_diff_y < th1 and angle_diff < th2
8       count=count+1
9       list [count]=( M_first_set ,M_second_set)
10 return list of minutie paired
```

where th1 and th2 represent the distortion tolerance thresholds.

III NEURAL NETWORK MODEL FOR IMAGE COMPARISON

Remarkable progress in the field of artificial intelligence has spawned a plethora of neural network architectures specialised for specific tasks. For fingerprint verification and image comparison, the adoption of Siamese models has emerged as a particularly effective approach [4,6]. The model we describe below is in this vein, adopting a Siamese architecture for image comparison, thus exploiting the advantages inherent in this convolutional structure.

Our methodology is based on the use of a neural network specifically designed for fingerprint recognition. The choice of this particular model, the details of which are set out below, stems from a series of considerations aimed at optimising recognition performance in a variety of contexts. Before exploring the characteristics of the network in depth, it is essential to emphasise the crucial role of methodology in evaluating the performance of fingerprint recognition methods.

To make our methodological approach more accessible, we will include a detailed schematic diagram here

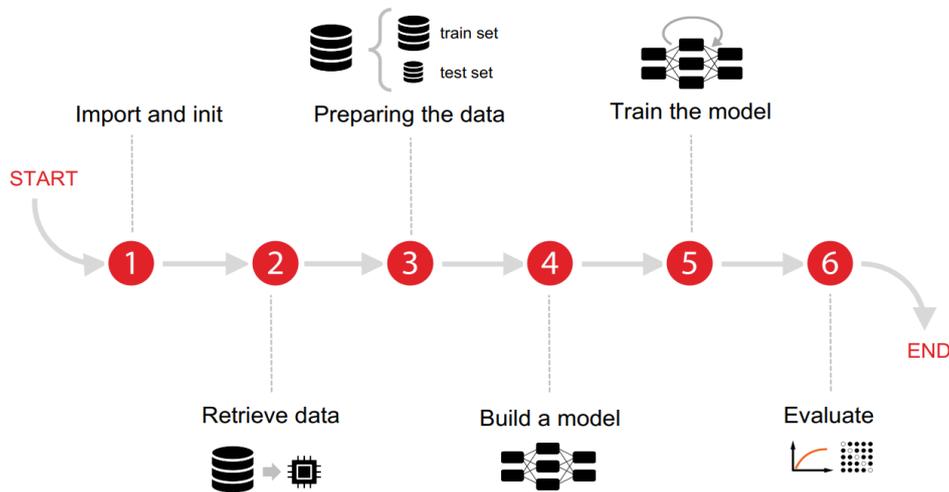


Figure 3: Diagram.

This diagram will provide readers with a clear view of the different stages in the process, from data preparation to the crucial minutiae comparison phase. The inclusion of this diagram is intended to provide a global perspective, making it easier to understand the interaction between the different components of our methodology.

3.1 Model architecture

The architecture of the fingerprint matching model is based on a Siamese approach. This method exploits two input branches sharing the same weights to extract distinct features from two fingerprint images, as illustrated in Figure 4. The main objective is to measure the similarity between these fingerprints, focusing on subtle differences [7]. The main objective is to measure the similarity between these fingerprints, focusing on subtle differences.

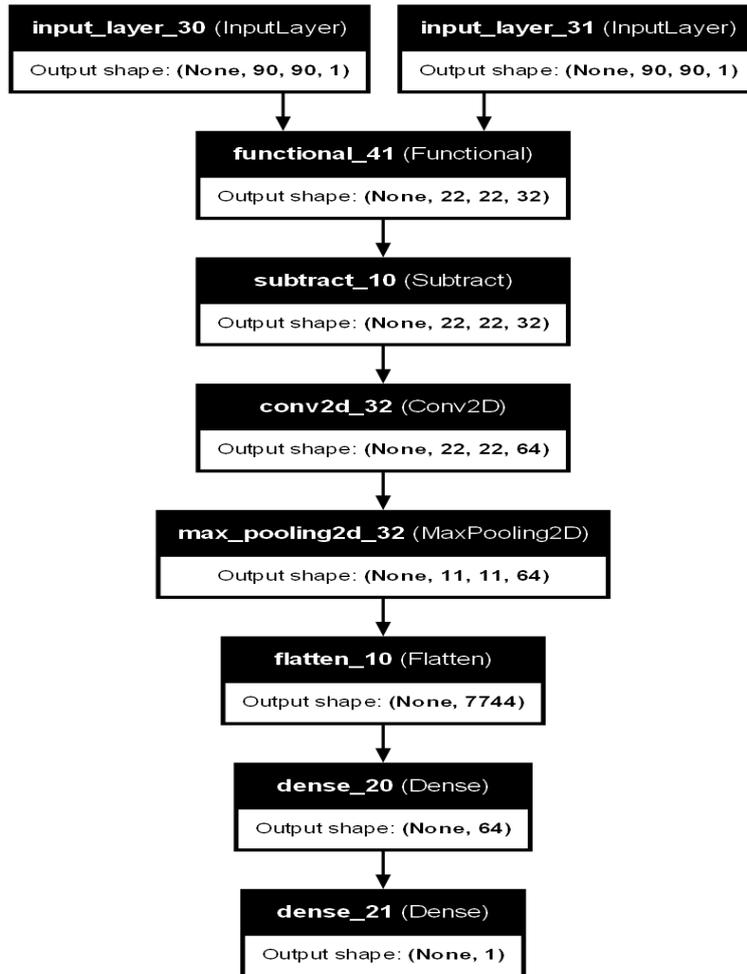


Figure 4: Model architecture.

3.2 Feature extraction

The first stage of the model involves feature extraction from fingerprint images. This phase uses convolution and max-pooling operations to detect significant patterns while reducing the dimensionality of the data. The special feature lies in the sharing of weights between the two input branches, ensuring consistent feature extraction.

3.3 Subtracting Features

Once the features have been extracted, a subtraction operation is performed between the two input branches. The aim of this step is to highlight the pixel-by-pixel differences between the fingerprints, highlighting areas of divergence.

3.4 Classification

The resulting features are then passed through classification layers, including additional convolution operations. These decision layers determine the probability of similarity between the fingerprints. The sigmoid activation function at the output layer produces a value between 0 and 1, indicating the degree of similarity.

3.5 Data Augmentation Training

To improve the robustness of the model, we integrated a data generator during the learning phase. This generator applies different augmentation techniques, such as Gaussian blur and geometric transformations, to diversify the dataset. In our case, we increased the number of images by five for each footprint. This additional increase is intended to further enrich the dataset, giving the model a greater variety of cases to deal with. This diversification is essential to enable the model to generalise better in the presence of variations in fingerprints, thus helping to improve its robustness and its ability to recognise fingerprints effectively in real-life situations. An example illustrating this increase in data is shown in Figure 5.

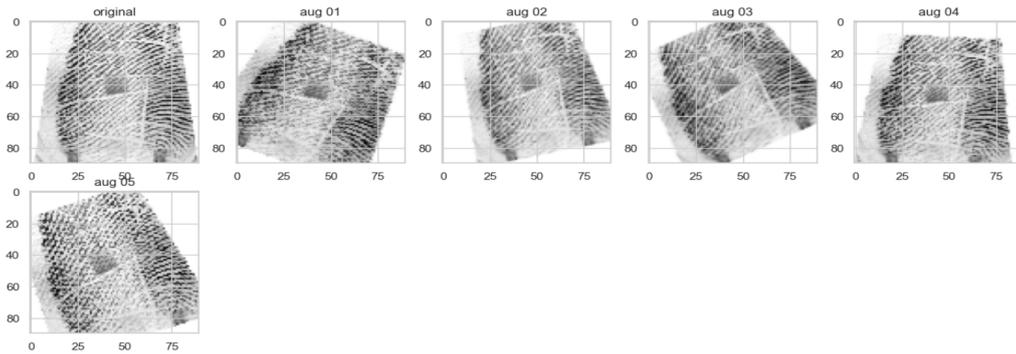


Figure 5: Data Augmentation.

With regard to the model parameters, the activation function used is ReLU (Rectified Linear Unit) for the convolutional layers, except for the output layer, which uses the sigmoid activation function. The optimizer used is Adam, an algorithm commonly used in deep learning, with the default learning rate. For the loss function, we opted for the binary cross-entropy loss, adapted to binary classification tasks. Finally, the batch size used for training is 563, determining the number of samples processed simultaneously before the model weights are updated. We also trained the model over 6 epochs, a number chosen to ensure adequate convergence while avoiding overlearning. A summary of the model is presented below:

Model: "functional_47"

Layer (type)	Output Shape	Param #	Connected to
input_layer_33 (InputLayer)	(None, 90, 90, 1)	0	-
input_layer_34 (InputLayer)	(None, 90, 90, 1)	0	-
functional_45 (Functional)	(None, 22, 22, 32)	9,568	input_layer_33[0]... input_layer_34[0]...
subtract_11 (Subtract)	(None, 22, 22, 32)	0	functional_45[0]... functional_45[1]...
conv2d_35 (Conv2D)	(None, 22, 22, 64)	18,496	subtract_11[0][0]
max_pooling2d_35 (MaxPooling2D)	(None, 11, 11, 64)	0	conv2d_35[0][0]
flatten_11 (Flatten)	(None, 7744)	0	max_pooling2d_35...
dense_22 (Dense)	(None, 64)	495,680	flatten_11[0][0]
dense_23 (Dense)	(None, 1)	65	dense_22[0][0]

Total params: 523,809 (2.00 MB)
 Trainable params: 523,809 (2.00 MB)
 Non-trainable params: 0 (0.00 B)

Figure 6: Model summary.

IV RESULTS

In our study, we used two distinct methods to analyse an image dataset: the Hough transform method and the neural network method.

For the Hough transform method, we randomly selected 628 images from our main dataset. This selection was used to create two subsets of the data, Data1 and Data2, containing 500 and 128 images respectively. Note that 64 images are common to these two subsets. We then compared the fingerprints in Data2 with those in Data1.

For the neural network approach, we divided our dataset (20,000 fingerprint images) by allocating 90% of the images to model training and the remaining 10% to validation. After training, a random sample of 128 images was selected for further testing. These tests were used to compare the results obtained with those of the Hough transformation.

These evaluations were carried out on a Lenovo Ideapad Gaming 3 laptop, equipped with 16 GB of RAM and a 10th-generation Intel Core i5 processor running at 4.5 GHz. Python (version 3.11.7) was used as the main development environment for implementing the machine learning models. TensorFlow (version 2.15.0) was used to create, train and evaluate neural networks, in particular for the Siamese neural network method. Anaconda was used as the development environment, with Jupyter Notebook for executing and presenting the Python code. All these operations were carried out on the same machine to ensure consistency of experimental conditions.

Thanks to these rigorous methodological approaches, we have obtained precise and reliable results, highlighting the distinct performance of each analysis method. The results are presented in the table 1.

These results are also illustrated using a confusion matrix and a diagram, providing a clear visualisation of the performance of each method.

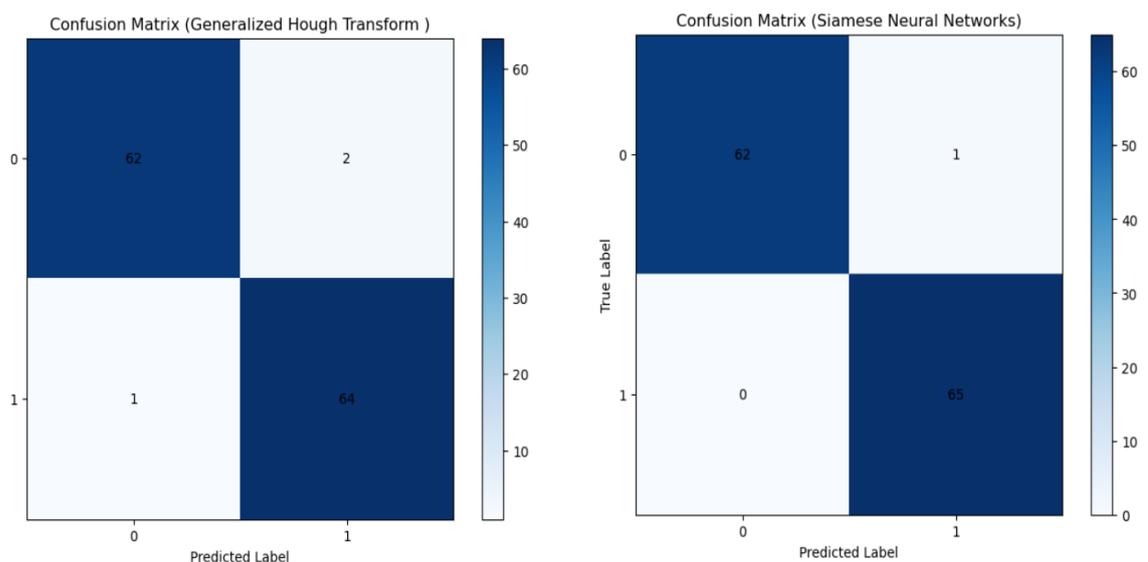


Figure 7: Confusion matrix.

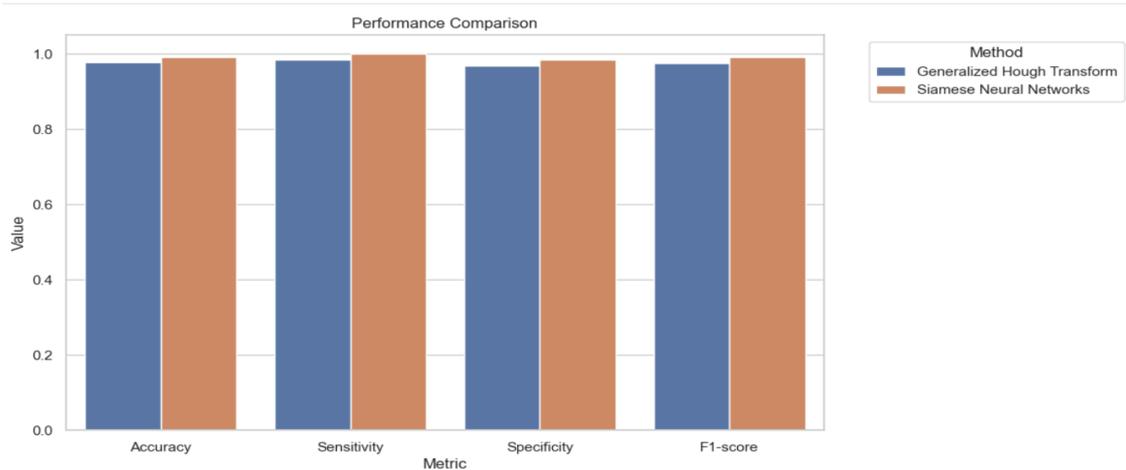


Figure 8: grouped bar graph of analysis method performance.

	Accuracy	Sensitivity	Specificity	F1-score
Generalized Hough Transform	0.977	0.984	0.969	0.976
Siamese Neural Networks	0.992	1.0	0.984	0.992

Table 1: Performance comparison of analyzed methods.

V DISCUSSION

5.1 Performance comparison

In this section, we compare the performance of the generalized Hough transform and neural networks, based on our results.

Our observations show that the neural network method slightly outperforms the generalized Hough transform. Indeed, the accuracy of neural networks is slightly higher (0.992) than that of the Hough transform (0.977). In addition, the perfect sensitivity of 1.0 of the neural networks demonstrates a remarkable ability to correctly identify positive fingerprints, while the sensitivity of the Hough transform is slightly lower (0.984). In terms of specificity, the two methods performed comparably well, with values of 0.984 for neural networks and 0.969 for the Hough transform. Finally, the F1 score, which assesses the balance between precision and sensitivity, is also slightly higher for neural networks (0.992) than for the Hough transform (0.976).

These results suggest that Siamese neural networks perform better for the fingerprint identification task than the generalised Hough transform method, particularly in terms of sensitivity and F1 score. However, it is important to point out that the Hough transform also performs well and can be a viable option in certain situations, particularly when computing resources are limited or when the available data is structured in such a way as to facilitate its use.

5.2 Limitations of the study

For an accurate interpretation of the findings of our study, it is essential to take into account its limitations. First, although the CASIA-FingerprintV5(BMP)2 database includes 20,000 fingerprint images, it represents only a fraction of the diversity of human fingerprints. Therefore, the models trained and evaluated on this database may not be fully generalizable to other datasets with a wider variety of fingerprints.

Secondly, our study focuses on the evaluation of two specific techniques: the generalised Hough transform and Siamese neural networks. Although these techniques were chosen for their relevance to fingerprint identification, other methods may offer different or complementary perspectives. Thus, our findings may not be generalizable to other fingerprint identification techniques.

Thirdly, the performance of the models we have developed may be sensitive to the parameters chosen during training, such as model hyperparameters and optimisation methods. Variations in these parameters could lead to different performances, requiring further exploration for a full understanding of the models' capabilities.

Finally, different experimental conditions, such as the hardware used, software libraries and versions of machine learning frameworks, may also influence the results. It is therefore crucial to take these factors into account when interpreting the performance of the models and their applicability in real-life contexts.

VI CONCLUSION

In conclusion, this comparative study examined the performance of the generalised Hough transform and Siamese neural networks in the field of fingerprint recognition, revealing significant results. Siamese neural networks, with an accuracy of 0.992 and an F1 score of 0.992, demonstrated a slight superiority over the Hough transform, which obtained an accuracy of 0.977 and an F1 score of 0.976, underlining the effectiveness of this approach in this specific context.

This comparison provides valuable information for researchers and practitioners in the field of fingerprint recognition, highlighting the strengths and limitations of each method. These findings are crucial in guiding the development and adoption of more accurate and robust biometric recognition technologies, helping to enhance security and privacy in a variety of applications. However, despite these promising results, it is important to note that challenges remain, such as improving resistance to variations in fingerprint quality and managing large volumes of data. Future research is therefore needed to further explore these issues and develop even more effective solutions in the field of fingerprint recognition.

In terms of future prospects, an interesting approach could be to explore the possibility of merging the two methods studied. By combining the robustness and speed of calculation of the generalised Hough transform with the precision and generalisation of Siamese neural networks, it would be possible to create a more powerful and adaptable hybrid approach. This fusion of methods could open up new avenues for further improving fingerprint recognition and responding to current challenges in the field.

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