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A Deep Learning Approach Based Contactless Fingerprint Recognition

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ABSTRACT

An important biometric technique is fingerprint recognition. Depending on the data-gathering approaches, fingerprints can be categorized into contact-based and contactless systems. Because of its advantages in security and sanitation and its small cost in now a day, contactless fingerprints have consistently attracted study interest. In this article, we present a technique for creating a contactless fingerprint identification system that uses an image sensor and a suitable environment to capture a finger image remotely. The obtained global and local attributes are applied to the acquired finger images. A Siamese convolutional neural network (S-CNN) extracts global information from a finger image. The proposed approach calculates matching scores using characteristics taken from CNN and minutiae. Fusing the two scores creates the last matching score between the investigation and reference fingerprint patterns. Most crucially, we can execute contactless fingerprint identification in present with minimal latency and adequate matching accuracy thanks to the Nvidia Jetson Nano development kit, which is employed to create the proposed approach. A 150-train subject and 120-test subject internal IITI contactless fingerprint dataset (IITI-CFD) are applied to evaluate the effectiveness of the recommended method. The proposed approach is better than existing approach.

Keywords: Contactless Fingerprint, Fingerprint Recognition, Siamese Convolutional Neural Network (S-CNN), Equal-Error Rate (EER), Score Fusion.

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1. INTRODUCTION

Fingerprint identification technologies for individual verification and authentication are growing today [1-2]. A lot of different authentication methods, and one of them is fingerprint identification. This technique is generally acknowledged and is currently employed in various applications on an authorized basis for user identification. The cybercrime department uses this fingerprint verification to identify criminals by using the fingerprints left in the appropriate places, similar to applying it to authenticate people so they can recognize them [3-4]. Various fingerprint verification techniques are utilized in the research, but none consistently produces accurate and effective results [5]. We are now using Convolutional Neural Networks (CNN) to increase the precision of our recommended fingerprint identification in contact-based and contactless fingerprint authentication systems; we are now using CNN [6-7]. Conventional authentication methods, such as usernames, security codes, swipe card identification, and others, have often fallen short of customer expectations. To upgrade the user demand with more efficient and accurate results, some high-level authentication technologies, such as face, iris, voice, and fingerprint recognition, came into existence at that time [8].

To match the presence of the offender, civil and law enforcement departments frequently utilize fingerprint identification out of the several verification techniques. In the rudimentary authentication techniques, practically all users attempt to match the input fingerprint photographs by pressing their fingers against hard surfaces [9]. Nevertheless, these more brutal substances occasionally result in partial or defective photos because of poor finger positioning. A significant difficulty in contact-based systems, this is growing in importance. To get exact answers without any issues, we try to replace the contact-based fingerprint verification with contactless fingerprint authentication [10].

Artificial neural networks are the source of a subset of machine learning techniques known as deep learning (DL). DL uses at least two hidden layers, compared to standard machine learning algorithms, which employ a concealed layer with input and output layers [11- 12]. Since current DL has numerous hierarchical layers of illustrations for learning features, the term "deep" in DL refers to hierarchical levels of words. According to the literature, DL outperformed classical methodologies or standard machine learning techniques [13]. The advantages of DL over conventional approaches include their ability to learn features instead of manually selecting them automatically, their deep hierarchical representations, and their capacity for representation dispersion large volumes of data may now be processed more quickly thanks to the emergence of powerful processor technology like image processing units [14].

The robustness of data-intensive DL was further illustrated by this, in cybersecurity research, DL techniques have been widely applied [15-16]. As an illustration, it has been discovered that the DL is used in digital security applications for user authentication and modelling biometrics in forensic science for criminal investigations. Now a days have seen an rise in interest in the uses of DL in biometrics recognition and authentication, with numerous techniques being established to address digital security and protection concerns [17-18]. Measuring physiological and behavioural traits for the automatic identification of people is known as biometrics. Systems of knowledge-based recognition are preferable to biometrics [19-21]. Individuals have been identified and given rights via biometric technologies based on their physiological and behavioural traits [22].

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2. RELATED WORK

Many Deep Convolutional Neural Network architectures are used in a contactless wrist vein detection system that is provided [23]. The Transfer Learning (TL) method is employed. This approach dramatically increased biometric efficiency and rapid identification times of under 300 milliseconds with less than 0.4% inaccuracy and up to 98% accuracy. A unique 2D contactless fingerprint matching method is provided for the fingerprint triplet-GAN methodology [24]. This end-to-end technique, which goes beyond the conventional fingerprint minutiae extraction, uses a triplet network and a GAN. The results of the experiments show that it can work with 2D contactless fingerprints with cutting-edge effectiveness.

Unconstrained genetic algorithms and global minutia topology provide the foundation of a reliable contactless fingerprint identification approach that is demonstrated [25]. The global minutia topology is considered in defining an innovative similarity matrix based on both minutiae and minutia pairs. To compare this method's performance to that of the most advanced techniques while evaluating it using two contactless fingerprints. The approach for pose-compensation and minutiae extraction is provided [26]. Our deep neural network-based solution is resilient to false minutiae and requires no picture augmentation compared to the traditional minutiae extraction methods. The evaluation of the recommended outline superior commercial software and older methodologies is confirmed by the replicable investigational outcomes specified this approach uses open datasets.

Using Siamese design and the reciprocal distance loss function, more accurate contactless to contact-based fingerprint recognition is attainable through a minutiae attention network. A worldwide branch that retrieves feature values is included in the presented approach, along with a unit for minutiae attention focusing on tiny minutiae regions [27]. The results on two openly accessible databases show notable performance gains over the traditional approaches works and confirm the efficacy of the recommended architecture for the transition from contactless to contact-based fingerprint recognition. The presentation is of a contactless fingerprint identification system that uses an image sensor in a proper setting to take a finger data at a distance. Afterward, additional processing is done on the collected finger data to extract global and local (minutiae-based) features [28]. The system is created with the help of the NVidia Jetson Nano development kit, which enables to carry out contactless fingerprint identification in present with minimal latency and satisfactory matching precision. An internal IITI-CFD databases with 110 training and 105 test participants is used to evaluate the outcome. Using the IITI-CFD, this method obtains an equal-error rate of 2.19%.

A fingerprint recognition structure designed on image processing techniques that enhance fingerprint outlines, employing machine learning techniques to speed up processing and improve the process' accuracy [29]. On the combined high- and low-quality fingerprint database, the outcome was 97.75%. The public domain contactless 3D finger knuckle database was compiled throughout two sessions and 130 participants. Comparative outcomes on this challenging 3D finger knuckle database utilizing cutting-edge feature extraction techniques show the efficacy of our strategy [30]. The superior performance on other publically accessible datasets employing the most recent pixel-wise 3D palm print and 3D fingerprint feature descriptors.

A framework based on CNN is proposed to compare contactless and contact-based fingerprint pictures successfully. Using fingerprint minutiae, the appropriate ridge

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map, and a particular region of the ridge map, our framework first trains a multi-Siamese CNN [31]. The results of comparing contactless to contact-based fingerprinting methods in the literature, as well as many popular deep learning architectures. The presentation of a database-based CNN framework for contactless fingerprint data recognition [32]. Framework trains a CNN first using fingerprint details and a specific ridge map region. The experimental outcomes produced in this research demonstrate the efficacy of the recommended strategy and highlight a significant advancement in fingerprint identification techniques. Moreover, the proposed solution helps to reduce fingerprint spoofing, increasing security.

3. PROPOSED METHODOLOGY

We have created a CFRS that consists of 3 main parts: a module for contactless finger data capture, a module for global feature matching using CNN, and a module for minute feature matching. The planned CFRS captures the finger. The Sony IMX219 8-megapixel Raspberry Pi NoIR camera V2 captures a distant data. The proposed CFRS uses a Raspberry Pi NoIR camera V2 with an 8-megapixel Sony IMX219 sensor to collect finger data from a distance. There is a shown a schematic diagram of the proposed approach. The proposed approach based on Siamese CNN workflow to proceed data using camera sensor. Generally, this network creates a set embedding length of the fingerprint data that is then used to determine how similar the probing and reference data are. Also, we used an image enhancement approach on the recorded finger data before doing minutia-based matching with the conventional. The final results are produced by combining the scores from the two courses. Also, using the standard NIST Biometric Image Software, we performed minutia-based matching on the acquired finger data after applying an image enhancement technique. The points from both modules are combined to arrive at the final score.

We developed new algorithms and modified traditional process to boost the accuracy of two fingerprint patterns. Then, we implemented the new hardware algorithms with the least latency. Contactless fingerprint data are generally difficult to work with because of issues including perspective distortion and deformation, which are covered in. Lightning effects impact the image quality and the number of fingerprint data can acquire. Figure 1 illustrated the proposed approach.

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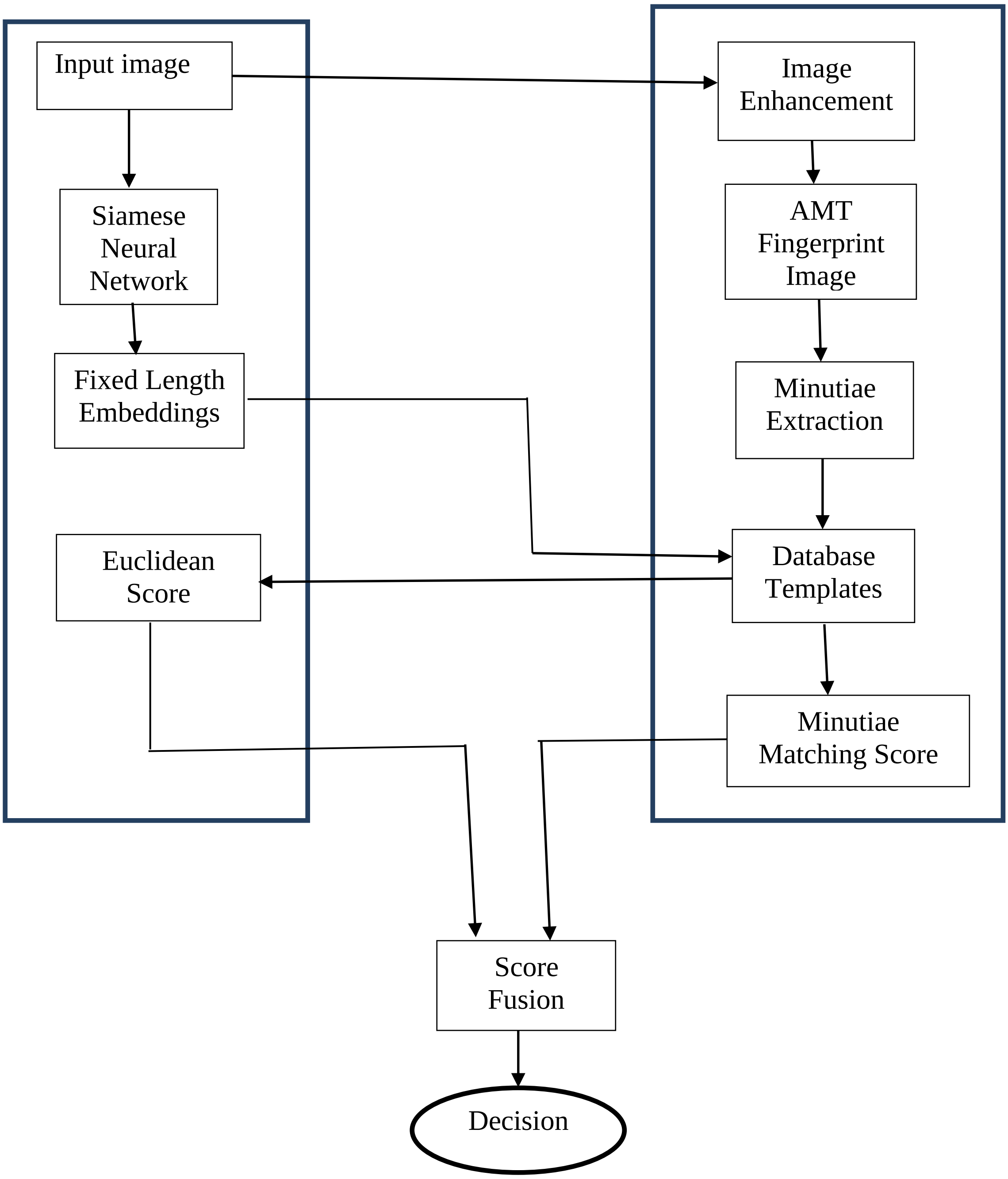

Figure 1: Proposed Workflow

We must consider both global and local features to extract the most data possible from a fingerprint data that the image sensor has acquired to avoid the problems above. Therefore, the proposed equivalent method based on deep learning to solve with global features. Later, we offer a complete explanation of every module involved in the proposed CFRS.

3.1 Minutiae-Based Approach

The data acquired by the sensor is less than that from images from contact-based sensors,

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the image enhancement component is crucial to the proposed CFRS. First, the ridge-valley map from the provided fingerprint data must be extracted. Adaptive mean thresholding (AMT) used to a grey-scale image that distinguish an exciting foreground from the background image. AMT operates under the premise that smaller picture regions have roughly constant illumination, making them better suited for thresholding than global thresholding. It can help with different illumination states in the fingerprint data, such as those caused by string glows, shadows, and gradients. Describes the thresholding technique's outcome. First, a thresholding technique is applied to the raw data. The ridge-valley map is then retrieved based on AMT after the basic idea has been transformed into a grayscale image. The AMT method performs better than global thresholding.

Local features, collectively called minutiae, include ridge termination and ridge bifurcation. We utilized the NBIS MINDTCT legal minutiae detector for minutiae extraction. It recognizes and keeps track of recordings of minutiae data. The matching process is subsequently carried out using the little data the MINDTCT algorithm collected. For minute matching, the NBIS fingerprint matching algorithm BOZORTH3 is specifically used. A fingerprint-matching algorithm based on minutia information computes similarity scores (F_n) using matched minutiae.

3.2 Deep Learning-Based Approach

The convolutional neural networks have recently demonstrated to be extremely effective for several computer vision tasks, particularly image classification. The proposed approach immediately feeds the raw fingerprint data from the sensor to a specially designed Siamese CNN. The fundamental rationale behind adopting CNN is that a fingerprint data contains many global features that CNN can quickly identify. The size of the data is the main issue that has to be addressed. Further down the network, the data size should not decrease since a fingerprint data has even designs that would be rendered useless if the data size decreased. To maintain the data size after applying each set of convolution layer filters. The convolution and dense layers were considered when building the Siamese architecture so that the architecture uses the fewest possible parameters. This is done to lessen the system's latency when installed on the hardware.

There could only be three convolution layers, each with four, eight, or eight filters and layers for batch normalization. An average pooling technique is used at the end of the convolution layers to pass through the thick layer with the fewest possible parameters**.** The Siamese CNN's architecture is employed in the proposed CFRS. A Siamese network is used to match and produce a matching score among a specified set of fingerprint patterns. Two identical CNNs with shared weights are used. With a distance-aware contrastive loss function, the neural network is trained to reduce the distance between two comparable patterns and maximize the space between two patterns. Equation (1) is denoted by contrastive loss function.

$$C = (1 - Z))\frac{1}{2}(E_d)^2 + (Z)\frac{1}{2}(max(0, n - E_v))^2 \rightarrow \quad (1)$$

Here Z is,

$$Z = \{1,\ similar\ class\ 0,\ dissimilar\ class \quad \rightarrow \quad (2)$$

E_d stands for Euclidean Distance, n stands for margin value.

3.3 Score Fusion

The minutiae matching element and the deep learning-based program produce their corresponding scores, equation (3) shown as F_n and F_i, respectively, as previously stated. F_s stands for score fusion. Before fusing these scores, min-max normalization is used to

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normalize each score to the range (0, 1). Lastly, a weighted total is calculated where v_i and v_n reflect the weights assigned to the results of minutiae matching-based and deep learning techniques. Analytically, these weights are v_n and v_i, were set at 0.4 and 0.6.

$$F_s = v_i F_i + v_n F_n \quad \rightarrow \quad (3)$$

4. RESULTS AND DISCUSSION

We have created a distinctive atmosphere for contactless data capture. A contactless fingerprint dataset known as IITI-CFD is gathered using this capturing environment. A total of 2300 fingers contributed 2000 finger data, each of which contributed eight impressions. The IITI-CFD is separated train and test datasets for training the CNN-based approach. The training set comprises explicitly 1000 finger data. From 110 different fingers. The test set is made up of the remaining picture from 200 fingers. The EER, FMR100, and FMR1000 performance measurements were applied to measure the evaluation of the present technique. Let T and I represent the stored pattern and the confirmation characteristics set, respectively. Genuine score distribution and imposter score are obtained to estimate the precision of the biometrics confirmation structure. The FMR (false match rate) and FNMR (false non-match rate) are the two verification error rates based on the threshold FNMR. The FMR is the proportion of fake pairings with comparison scores above the threshold, and FNMR is the proportion of real pairs below the threshold. The error rate at the point where both the FMR and FNMR are equal is known as EER. The higher the precision of the biometric method, the lower the equal error rate value. The system's evaluation is typically testified by showing the (receiver operating characteristic) ROC curve or the (detection error trade-off) DET curve, all operating points. The ROC curve visually denotes the trade-off between the FMR and the 1-FNMR. Contrarily, the DET curve illustrates the exchange between the FMR and FNMR. Calculating the proposed system's FMR100 and FMR1000 specifically uses the DET curve.

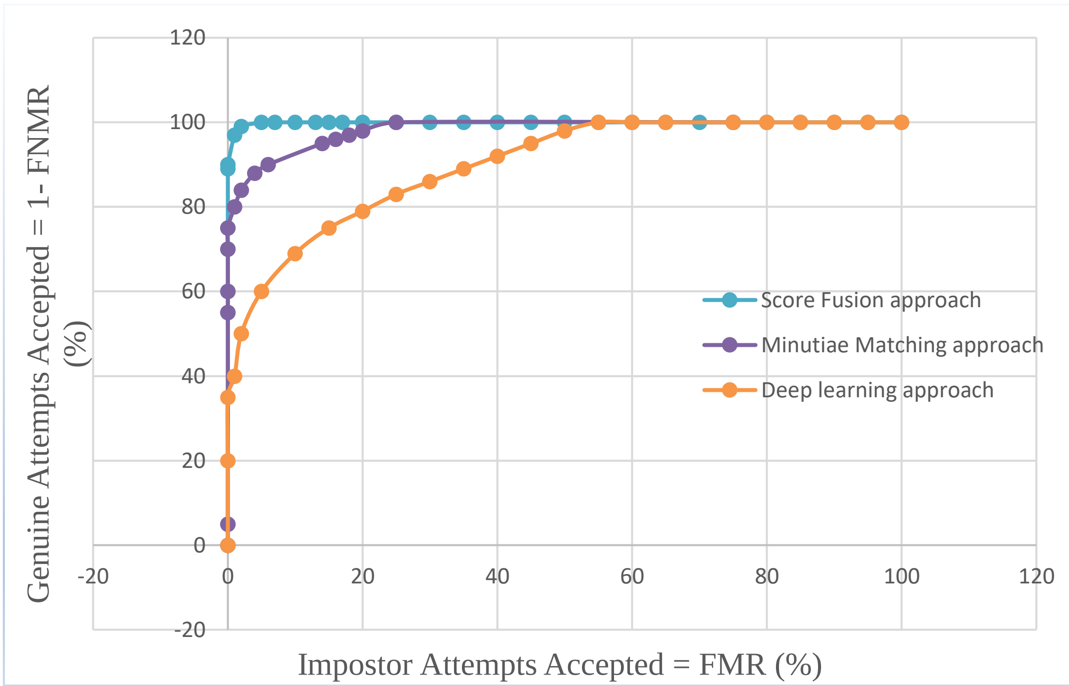

Figure 2: Comparison of Different Approach Using ROC

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Figure 2 displays the ROC curves for the proposed method. Combining the deep learning-based technique with the minutiae-based method at the score level yields better outcomes than doing so separately.

Table 1: Comparison of EER

Approach	EER
Minutiae Matching	3.02%
Score Fusion	1.98%
Deep Learning	10.20%

Table 2: Comparison of FMR100 and FMR1000

Approach	FMR100	FMR1000
Minutiae Matching	0.072	0.123
Score Fusion	0.026	0.102
Deep Learning	0.421	0.762

Tables 1 and 2 show the EER, FMR100, and FMR1000 values generated for the test dataset using each of the three procedures. They indicate that when the deep learning score is combined with cutting-edge NBIS software, the results are superior to those obtained using each methodology separately. The fused score value is then compared to a threshold to establish the final evaluation of the developed biometric structure.

5. CONCLUSION

This paper outlines the foremost problem of the contact-based biometric system and its potential benefits. Deep learning models can increase matching accuracy even more in addition to conventional image processing and cutting-edge feature extraction technologies. The contactless area has a huge market potential due to computation and sensing technology advances. Our findings demonstrate that contactless biometric devices can reach the same level of accuracy as other systems advertised on the market. Further study will involve embedding our established model with an image sensor and an environment for image capturing on a printed circuit board (PCB) and implementing it on a microcontroller and GPU for quicker calculation. In this approach, the potential of our designed model as an independent embedded device would be realized.

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