An Advanced Fingerprint Recognition Using Hybrid Deep Learning

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Abstract:- The effectiveness of fingerprint recognition largely depends on detecting valid minutiae. Various systems and techniques have been developed to reduce false detection rates and improve performance. This research focuses on enhancing fingerprint verification and classification through feature extraction and learning models. The study uses the FVC2002 dataset, which includes around 72 images with blurs and distortions, for training and testing. By employing Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) models, the research achieved approximately a 2.5% improvement in performance over existing methods.

Keywords- Biometric systems, Finger print, Convolutional Neural Networks, Bidirectional Long Short-Term Memory

I. INTRODUCTION

Biometric systems can be used for either verification or identification. In verification, the system associates an individual with a unique identifier (like a PIN or username) and confirms their identity by comparing the input template with the specific template linked to that identifier in the database. Identification systems, on the other hand, compare the input template with all stored templates to determine the individual's identity. Fingerprint is the most interesting and oldest human identity used for recognition of individual. In the early twentieth century, fingerprint was formally accepted as valid signs of identity by law-enforcement agencies. After all, pieces that need proof can often be difficult, if not impossible. In most cases under these circumstances, conventional photographic techniques have been successfully used to record such evidence discovered on the scene.

Machine learning is a process applied on data, having previously unknown information which may be useful for taking some decision. More precisely we can say that it works on the large datasets from databases to extract the relevant patterns which may help to design different strategies for a profitable business. Association rules, Support Vector Machine (SVM), Artificial Neural Network (ANN) and Decision Trees (DT) are commonly used machine learning techniques using which researchers have proposed many churn prediction models. The results of the machine learning algorithms are more accurate than the results produced by direct programming. These algorithms are able to examine large amounts of data. This requires you to think about the process of preparing the model and choose the one that is best for your problem and that is suitable for getting a good result.

II. LITERATURE REVIEW

Ahmeed et al. [1] proposed a new fingerprint classification method, using Discriminant Analysis, Gaussian Discriminant Analysis, and HOG and SFTA feature vectors, has been tested on the Sokoto Coventry Fingerprint Dataset, achieving 99% classification accuracy.

Ametefe et al. [2] developed a fingerprint pattern clasifier using deep transfer learning and data augmentation, achieving classification accuracy of 98.2%, 97%, and 97.8%, compared to 93.9%, 93.7%, and 92% without data augmentation. Gams et al.[3] proposes a deep learning strategy using pre-trained convolutional neural networks to identify male or female fingerprints, outperforming previous methods in accuracy, execution time, and efficiency.

Uniqueness: Fingerprints are unique; no two people can have the same fingerprint; Stability: Fingerprints are very stable and will not change easily with time and age; Performance: The use of fingerprint-based recognition technology can satisfy the accuracy of recognition, the need for recognition speed and recognition robustness with less storage and computational overhead [4].

Toki et al. [5] explores the use of machine learning algorithms on biometric SmartSpeech datasets for early detection and evaluation of children at risk of neurodevelopmental disorders and communication deficits, revealing GenClass as a top competitor. Zhang et al.[6] explores the use of neuroimaging techniques to extract brain fingerprints for reliable identification and activity detection, analyzing their advantages, disadvantages, application trends, and potential research areas.

Mahmoud et al.[7] proposes an automatic deep neural network (ADNN) model for fingerprint recognition, aiming to improve accuracy in forensic and security fields. The model automatically specifies the neural network architecture and parameters like filters, epochs, and iterations. It guarantees 99% accuracy by updating itself until it stops and outputs the result. The system is fully automated, allowing users to input initial parameters and updating until optimal results are achieved. The ADNN can recognize people from thumbs and fingers and recognize distorted samples.

Yu et al.[8] explores fingerprint acquisition techniques, discussing pros, drawbacks, and limitations, and their potential for IoT applications, focusing on optical capacitive and ultrasonic methods.

Cao et al. [9] discussed the preliminary knowledge of fingerprint rib structures is encoded with respect to orientation patch dictionaries and continuous phase patches to improve fingerprint reconstruction. The alignment patch dictionary is used to reconstruct the alignment field from the minutiae while the continuous phase patch dictionary is used to reconstruct the peak model. The experimental results of three public domain databases (FVC2002 DB1_A, FVC2002 DB2_A and NIST SD4) show that the proposed reconstruction algorithm overcomes the last reconstruction algorithms in terms of properties: 1) incorrect precision and 2) performance compliance type I (reconstructed fingerprint mapping on the same original fingerprint as the minutia) and type II attacks (associating the reconstituted imprint with another imprint of the same finger).

Chhabra et al. [10] proposed an early fingerprint distinction technique based on colour and saliency masks . A breakthrough in fingerprint segmentation uses optimal resources, detecting relevant areas with color and saliency masks. This hybrid approach, similar to object detection and classification, achieves 98.45% segmentation accuracy on the IIIT-D database.

Rezaei explored [11] an efficient algorithm for fingerprint recognition based on hybrid features of Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and moment methods. The proposed technique can be applied for high accuracy fingerprint recognition task in biometric systems.

Wei et al. [12] discusses the RSSI-based location fingerprinting method in indoor positioning algorithms, comparing common techniques and algorithms. It discusses improvement methods like signal filtering, received signal clustering, and location fingerprint matching optimization, providing a reference for selecting suitable algorithms for complex environments.

Zhang et al. [13] discusses recent research on molecular fingerprint detection using Raman and infrared spectroscopy for cancer diagnosis. Raman spectroscopy is an essential tool for studying molecules and their interactions, accurately diagnosing various types of cancer. Infrared spectroscopy complements Raman spectroscopy, detecting a wide range of biomolecules at low concentrations in complex biological samples. The article concludes with a comparison of the techniques and insights into future directions.

III. PROPOSED METHODOLOGY

In order to gain above mentioned objectives, FVC2002 dataset is taken for training and testing. In this dataset there are approx. 72 images which are used for testing purpose. In this dataset there are some blur, distorted as well as partial images also which are considered for recognition. The algorithm is designed to match with given training dataset that gives matching result in probability.

The flowchart of the proposed fingerprint recognition methodology consists of the following steps:

Input fingerprint image: The fingerprint image is provided as the input.

CNN Filter application: A CNN filter is used to enhance the image quality, especially if the image is blurred or distorted.

Feature extraction: Minutiae features, such as ridge endpoints and bifurcations, are extracted from the fingerprint image.

BiLSTM network training: The proposed BiLSTM (Bidirectional Long Short-Term Memory) network is trained on the extracted features and used to classify the fingerprint.

Performance evaluation: The performance of the algorithm is assessed using parameters such as the True Detection Rate, False Detection Rate, and Peak Signal-to-Noise Ratio (PSNR).

Each of these steps plays a crucial role in enhancing the accuracy and reliability of fingerprint recognition.

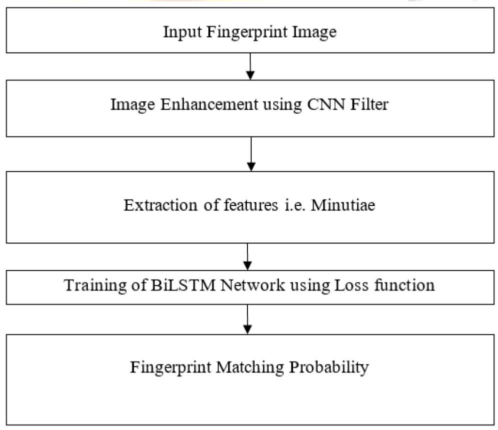


FIGURE 1: FLOWCHART OF PROPOSED METHODOLOGY

With the dataset, the proposed work will designed a CNN Filter and feature extractor In a Convolutional Neural Network (CNN), filters and feature extractors play crucial roles in identifying patterns and features within data, particularly in images. A filter, also known as a kernel, is a small matrix that slides over the input data (such as an image) to perform convolution operations. Each filter is designed to detect specific features, such as edges, corners, or textures. As the filter moves across the image, it multiplies its values by the corresponding pixel values, then sums them up to create a feature map. This process highlights the presence of the feature the filter is trained to detect.

Bidirectional Long Short-Term Memory (BiLSTM) is an extension of the Long Short-Term Memory (LSTM) network, designed to capture patterns from both past (backward) and future (forward) context in sequential data. LSTM is a type of Recurrent Neural Network (RNN) capable of learning long-term dependencies through the use of memory cells. Each LSTM cell has gates (input, forget, and output) to control the flow of information, making it effective in mitigating the vanishing gradient problem common in traditional RNNs. Forward Pass: One LSTM layer processes the input from start to end (left to right), capturing the context from past to present. Backward Pass: Another LSTM layer processes the same input from end to start (right to left), capturing future to past context

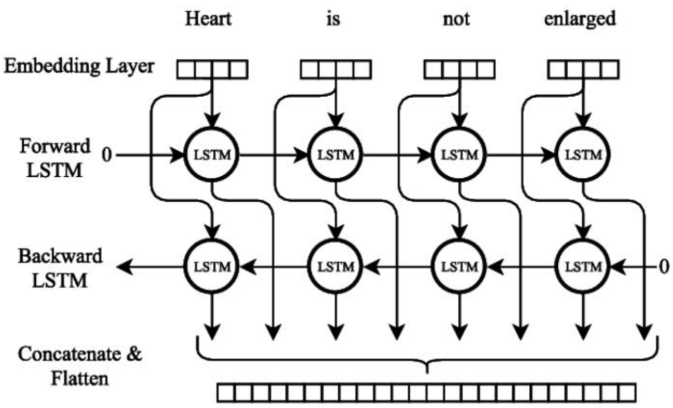


FIGURE 2: BIDIRECTIONAL LONG SHORT-TERM MEMORY (BILSTM) UNITS

$$i_t^{fwd} = \sigma(W_i^{fwd} x_t + U_i^{fwd} h_{t+1}^{fwd} + b_i^{fwd}) \quad (1)$$

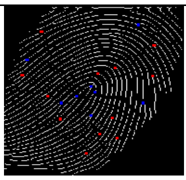
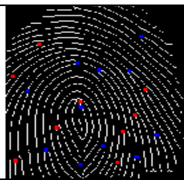
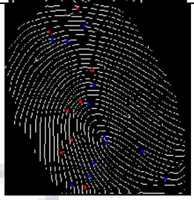
$$f_t^{fwd} = \sigma(W_f^{fwd} x_t + U_f^{fwd} h_{t+1}^{fwd} + b_f^{fwd}) \quad (2)$$

$$o_t^{fwd} = \sigma(W_o^{fwd} x_t + U_o^{fwd} h_{t+1}^{fwd} + b_o^{fwd}) \quad (3)$$

IV. RESULT ANALYSIS

In this section, result of different fingerprints are shown in below table 1 for performance evaluation of the proposed methodology.

TABLE 1: RESULT ANALYSIS

Input Image	Extracted Features	TDR	ERD	PSNR
		0.88	0.35	11.26
		0.71	0.21	11.75
		0.89	0.12	12.65

In [14] author presented a complete crime scene fingerprint identification system using deep machine learning with Convolutional Neural Network (CNN). The features of preprocessed data are fed into the CNN as input to train and test the network. The experimental results demonstrated the accuracy of 80% recognition a partial or full fingerprint in the criminal database.

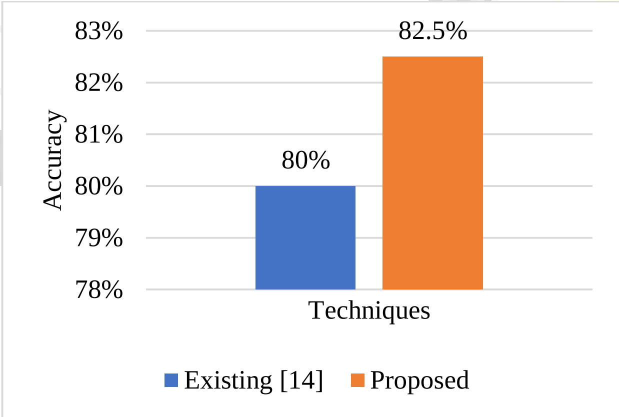


Figure 4: Comparative Performance Evaluation

Figure 4 represents the comparative performance evaluation of proposed CNN filter and feature extractor-based LSTM classifier with respect to existing work for fingerprint recognition.

V. CONCLUSION

This research focuses on developing a fingerprint identification and recognition system using biometric technology. The system is divided into two main parts: image processing and recognition. Fingerprint images from the FVC2002 dataset undergo various enhancements in the image processing stage, including gray level enhancement, spatial filtering, image sharpening, edge detection, segmentation, and thinning, using a convolutional neural network (CNN). After processing, minutiae and CNN features are extracted and used to train an BiLSTM classifier. The system is capable of recognizing pores in small image blocks and achieves efficient detection for partial fingerprints. The evaluation is based on accuracy, error detection rate, and PSNR value, with an accuracy of approximately 83%, which is a 2.5% improvement over previous methods.

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