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Utilizing Convolutional Neural Networks for Fingerprint-Based Attendance Monitoring

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ABSTRACT: The traditional method of taking attendance using paper sheets is prone to errors like impersonation, loss, or theft. To solve this issue, automatic attendance systems utilizing identification technology such as barcode badges, electronic tags, touch screens, magnetic stripe cards, and biometrics have been implemented. Biometric technology uses physiological or behavioral characteristics for identification purposes, but traditional biometric systems have limitations such as vulnerability to damage or alteration over time, and variations in occlusions, poses, facial expressions, and illumination can affect face recognition accuracy. Fingerprint identification relies on the distinctiveness of fingerprints and involves comparing two impressions of the friction ridges on human fingers or toes to determine if they belong to the same individual. There are five primary categories of fingerprints: arch, tented arch, left loop, right loop, and whorl. Various algorithms have been developed to recognize fingerprints using minutiaebased matching, which involves identifying key features like ridge ending and bifurcation. Deep learning algorithms, particularly convolutional neural networks, have been successful in improving identification accuracy by extracting features automatically from fingerprint images. In recent times, securing personal data has become increasingly important, and the Convolutional Neural Network (CNN) identification system is recommended for improving accuracy and performance. This paper proposes a fingerprint identification system that combines three models: CNN, Softmax, and Random Forest (RF) classifiers. The conventional system uses K-means and DBSCAN algorithms to separate the foreground and background regions and extracts features using CNNs and dropout approach. The Softmax acts as a recognizer. The proposed algorithm is evaluated on a public database and shows promising results, providing an accurate and efficient biometric identification system.

KEYWORDS: Fingerprint Identification, Convolutional Neural Network, Attendance Monitoring

I. INTRODUCTION

Attendance holds significant importance in academic institutions and organizations for multiple reasons such as maintaining records, evaluating students, and encouraging regular attendance. In most educational institutions in developing countries, there is a requirement for a minimum percentage of attendance, which is not always followed due to the challenges posed by the current method of taking attendance. This conventional method involves the use of paper sheets or registers for recording attendance, which is prone to errors like impersonation, loss or theft of the attendance sheet [1]. Nowadays, the swift advancement of technology has been utilized to streamline work processes. Tasks that were traditionally performed by humans can now be automated through systems, such as an automatic attendance system implemented in schools. Instead of relying on manual or signature-based attendance procedures, some systems utilize automated identification technology [2]. By utilizing barcode badges, electronic tags, touch screens, magnetic stripe cards, and biometrics (such as fingerprints, retinal scans, and facial features), an automated system removes the necessity for paper tracking. This simplifies the process for users as their attendance are recorded automatically when they enter and exit the school premises. This eradicates the likelihood of timesheets being lost or tampered with [3]. The significance of personal identification technology is increasing in security systems. Traditional authentication methods like keys, passwords, and magnetic cards are not secure enough since they can be lost or easily forgotten. To enhance security, biometric technology has been integrated into various systems, including door control systems, public systems, and PC login. Biometric technology is a technique that utilizes inherent physiological or behavioral characteristics for identification purposes [4]. In today's world, ensuring the security of information has become a top priority for individuals. Traditional biometric personal identification systems, which rely on physiological characteristics and behavioral patterns like faces, irises, or voice, have several limitations. These features can be imitated due to the human eye's ability to perceive physical appearances. Moreover, the features are vulnerable to damage or alteration over time. The use of iris recognition is often considered less user-friendly due to the discomfort caused by the brightness of the light during the biometric capture process. Additionally, face recognition accuracy is influenced by variations in occlusions, poses, facial expressions, and illumination [5]. Table 1 summarizes the characteristics of the aforementioned methods:

Table 1: Summary of characteristics of existing biometric system.

Biometric Trait	Main Advantage	Defect	Security Level	Sensor	Cost
Voice	Natural and convenient	Noise	normal	Noncontact	low
Face	Remote capture	Lighting conditions	Normal	Noncontact	Low
Fingerprint	Widely applied	Skin	Good	Contact	Low
Iris	High precision	glasses	Excellent	Noncontact	High

A complete imprint of a fingerprint can be deliberately obtained by transferring ink from the skin's friction ridges onto a clean surface, like white paper. Fingerprint identification involves comparing two impressions of the friction ridges on human fingers or toes to determine if they belong to the same individual. This identification technique relies on the distinctiveness of fingerprints, which implies that no two finger or palm prints are identical in every aspect [6]. Toward the end of the seventeenth century, European scientists began publishing their research findings on human skin. Dr. Nehemiah Grew was the first to describe the patterns of ridges, furrows, and pores present on the surface of the hands and feet in great detail. This was published in the Philosophical Transactions of the Royal Society of London in 1684 [7]. In 1880, Faulds submitted a paper to the journal Nature, where he demonstrated the distinctiveness and permanence of fingerprints [8]. There are five primary categories of fingerprints: arch, tented arch, left loop, right loop, and whorl. The algorithm used to analyze fingerprints identifies and extracts specific points, such as cores and deltas, from the fingerprint image. Based on the number and locations of these singular points, the algorithm can classify the fingerprint into its appropriate category [9]. There are various ways to identify a person, and biometrics have been one of the most secure options so far. They are virtually impossible to imitate by anyone other than the desired person. They can be divided into two categories: behavioral features, which are actions that a person can uniquely create or express, such as signature and walking rhythm; and physiological features, which are characteristics that a person possesses, such as fingerprint and iris pattern. Many works revolve around recognition and categorization of such data including, but not limited to, fingerprints, faces, palm prints and iris patterns [10]–[14]. Fingerprints have found numerous uses in fields like forensics, transaction verification, and unlocking mobile phones. To recognize fingerprints, many algorithms rely on minutiae-based matching, which involves identifying key features like ridge ending, bifurcation, and short ridge on the ridges of the fingerprint. In the past, there have been various attempts to recognize fingerprints using manually designed features, followed by classification. In [15], Park proposed a fingerprint recognition system based on SIFT features. In [16], Cappelli introduced a novel approach to representation using a 3D data structure created from minutiae distances and angles, which he called Minutiae Cylinder-Code (MCC). More recently, Minaee et al presented a technique for fingerprint recognition that employs multi-layer scattering convolutional networks. This method dissects fingerprint images using wavelets with various scales and orientations [17].

Currently, the majority of popular fingerprint identification algorithms rely on pre-defined conventional fingerprint characteristics, such as orientation field and singular point, which are artificially established. [18], [19]. Nonetheless, since these algorithms depend heavily on pre-established features, the identification accuracy may suffer in cases of high image noise, where the artificial features cannot be effectively extracted [20], [21].

In this regard, convolutional neural networks (CNNs) have been immensely successful in multiple computer vision and natural language processing (NLP) tasks in recent times [22]. Their success is mainly due to three factors: the availability of large-scale manually labelled datasets; powerful processing tools (such as GPGPUs); and good regularization techniques (such as dropout, etc.) that can prevent the over fitting problem.

Deep learning has been employed to tackle various problems, including but not limited to classification, segmentation, superresolution, image captioning, emotion analysis, face recognition, and object detection. Compared to traditional approaches, deep learning has demonstrated a considerable improvement in performance [23]–[31]. It has also been used heavily in numerous NLP tasks, including sentiment analysis, machine translation, name-entity-recognition, and question answering [32]–[35]. What is particularly fascinating is that certain deep architectures have features that can be effortlessly transferred to other tasks. This implies that one can extract features from a trained model for a specific task and apply them to a different task by training a classifier or predictor on top of them [36].

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J. Chandramohan and colleagues have created a fingerprint recognition system that utilizes minutiae-based fingerprint algorithms in various techniques. This method primarily involves extracting minutiae points from model fingerprint images and then matching fingerprints based on the number of minutiae pairings between them. The authors of this paper also outline a method for designing a fingerprint-based student attendance system with the aid of GSM. In this system, a tracking module is used to identify the whereabouts of a missing person [37].

Stephane Kouamo and Claude Tangha have developed a method for using fingerprint recognition as a reliable biometric technique for identification and authentication applications. The proposed method involves the use of a neural network for authenticating individuals accessing an automated fingerprint system for E-learning. During the training stage, the back propagation algorithm is applied to a multilayer perceptron, which includes a hidden layer that allows the network to calculate probabilities on templates that are invariant to translation and rotation. The results of the study, which were obtained from both the NIST special database 4 and a local database, indicate that the proposed method performs well in some cases [38].

Convolutional Neural Network (CNN) is a type of artificial neural network, mainly used in computer vision [39]. CNN is applied in many fields of fingerprint analysis, such as fingerprint classification [40], [41], fingerprint distortion rectification [42], overlapped fingerprint separation [43], and fingerprint identification [44], [45].

In criminal investigations, fingerprints play an essential role in identifying individuals. Nevertheless, there are still issues in the multi-fingerprint overlapping identification work for criminal investigation. Yih Chi-Hsiao et al. use CNN to train a network for overlapping fingerprint partitioning work. They achieved good results on both single-fingerprint and multi-fingerprint recognition [43].

II. FINGERPRINT IDENTIFICATION BASED ON CONVOLUTIONAL NEURAL NETWORK

The biometric recognition system typically consists of four key stages. The first stage involves the acquisition of the biometric trait, which entails obtaining a digital image of an individual using a specific capturing device. The second stage is the preprocessing stage, which aims to enhance the overall quality of the captured image. The third stage involves the extraction of feature data using various algorithms. Finally, the matching of the extracted features is typically carried out to perform the recognition of the individual.

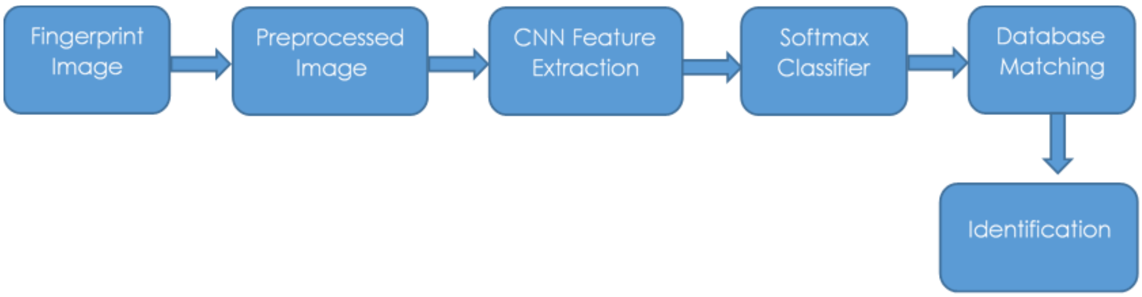

Figure 1: Block diagram of the proposed system

Image Acquisition

Various techniques exist for acquiring fingerprints, with the inked impression method being the most widely used. However, inkless fingerprint scanners are also available which eliminates the need for digitization. The quality of the fingerprint itself is crucial, as it has a direct impact on the accuracy of the minutiae extraction algorithm.

Fingerprint Image Enhancement

The orientation field of a fingerprint image is an intrinsic property that has been utilized in various methods to estimate it. The local orientation field filter-based or Gabor filter-based enhancement algorithms have been proposed for this purpose. The orientation field filtering techniques rely on accurate estimation of local ridge orientation, but this may not always be possible in low-quality fingerprint images, limiting their effectiveness. In contrast, Gabor filter-based techniques are more reliable, but computationally expensive, making them unsuitable for on-line fingerprint recognition systems like AFIS [46].

Fingerprint Recognition System

The following section provides a detailed description of the fingerprint recognition system using CNN-Softmax. The proposed method consists of three main stages: (1) pre-processing the fingerprint image; (2) extracting features using a CNN model; and (3) using Softmax as a classifier. The pre-processing step involves using the Soble and TopHat filtering method to enhance the image quality by limiting the contrast. Following the pre-processing step, the K-means and DBSCAN methods are utilized to segment the image into two regions: foreground and background [47]. The next step after pre-processing the fingerprint image is feature extraction, which is performed using a CNN architecture. To extract the region of interest (ROI) of the fingerprint, the Canny method [48] and the inner rectangle are used. The CNN is a type of neural network that uses deep supervised learning and convolutional layers. Essentially, the CNN can function as both a trainable classifier and an automatic feature extractor [49]. As shown in Fig. 2, the proposed fingerprint-CNN architecture is made up of five convolutional layers and three max-pooling layers, as specified in its configuration details which can be computed using Eq. (1). In addition, three rectified linear unit (ReLU) are used to our system which can be defined as Eq. (2).

$$O_n = \sum_{i=1}^{N-1} x_i f_{n-i}$$

Equation 1

where O is the output map, x is input map, f is the filter and N is number of elements in x.

$$f(x) = \max\,(0, x)$$

Equation 2

where x is the input to a neuron.

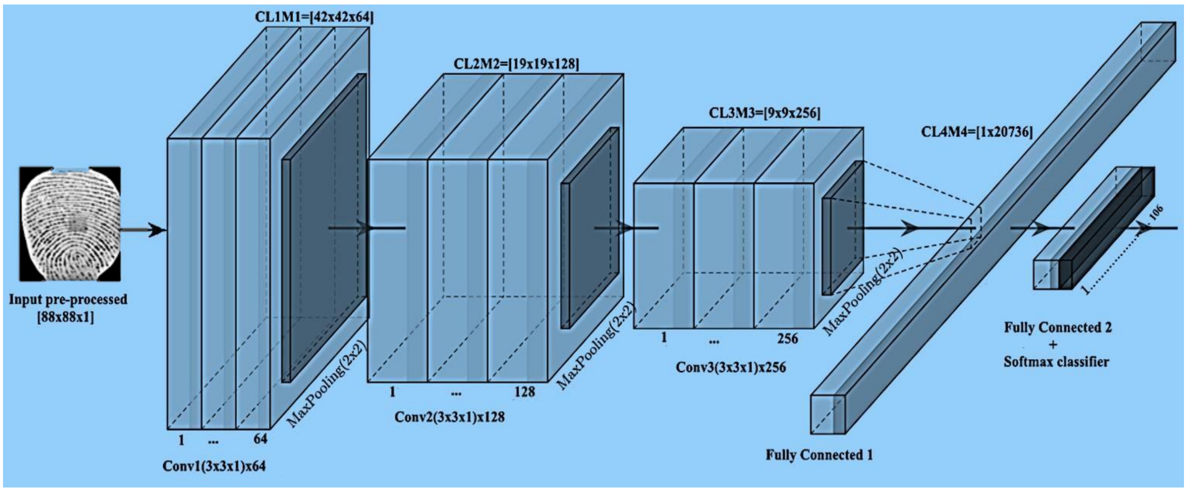

Figure 2: The Architecture of the proposed fingerprint-CNN model.

The Softmax function can be used to the fully convolutional layer output, as shown in Eq. (3).

$$S(r, i) = -\log\left(\frac{e^{z_i}}{\sum_{k=1}^{N} e^{z_j}}\right)$$

Equation 3

When the vector of output neurons is set to r, the probability of the neurons appropriate to the ith class is provided by separation the value of the ith (i = 1…j) element by the sum of the values of all elements.

The structure is described as follows: (1) L1: the input layer data size of 88 × 88, which is the size of input pre-processing fingerprint images; (2) L1M1: first hidden layer, composed by 64 convolutional filters of size 3 × 3 × 1, ReLU activation function and a max-pooling layer of size 2 × 2. This layer changes the input data into CL1M1 = (42 × 42 × 64) features; (3) L2M2: second hidden layer, composed by 128 convolutional filters of size 3 × 3 × 64, ReLU activation function and a max-pooling layer of size 2 × 2. This layer changes the input data into CL2M2 = (19 × 19 × 128) features; (4) L3M3: third hidden layer, composed by 128 convolutional filter of size 3 × 3 × 128, ReLU activation function and a max-pooling layer of size 2 × 2. In order to disconnect the connections between the first layer and the next layers the dropout probability of 20% is adopted. This layer transforms the input data into CL3M3 = (9 × 9 × 256) features; (5) L4M4: forth hidden layer namely fully connected layer, represented the flattening process, which is converted all the resultant two-dimensional arrays into a single long continuous linear vector. The features size of input data is 1 × 1 × 20,736; (6) L5M5: final hidden layer. The Softmax function is used to predict labels of the input patterns.

Data augmentation

Data augmentation is a technique that can address overfitting issues in CNN architecture. By applying transformations such as image translation, rotation, and cropping, the amount of training data can be increased. This method has been used effectively in many previous studies to augment data. We implemented the data augmentation as expand to the work in [50] such as the rotation and the translation (left, right, up and down) [51].

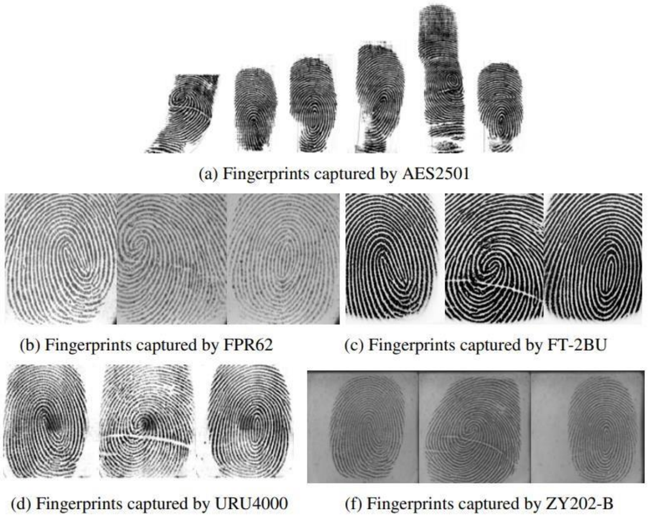

Figure 3: Sample images in the fingerprint database

III. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental operation platform in this study is described as follows: the host configuration: Intel Core i7 − 8565U Processor (8MB Cache, up to 4.6 GHz) and NVIDIA GeForce GTX 980 4GO GPU, runtime environment: Windows 10 home (64 bit). In order to better verify our algorithm, the following classification methods are adopted in the experiment: support vector machine (SVM) [52], RF [53], logistic regression (LR) [54]. The algorithms were pitted against one another and, to verify the proposed algorithm's effectiveness, the outcomes were evaluated on the SDUMLA-HMT [55] database which includes real multimodal data of fingerprint, finger vein and face images. The total number of fingerprint images was 25,440 we divided them into training, validation and test sets. The divided data set used in the experiment is shown in Table 2.

Table 2: Dataset structure of fingerprint

SDUMLA-HMT database	
Class number	5
Image number	25,440
Training	20,352
Validation	2,544
Test	2,544

The performance measure is the accuracy rate as defined by Eq. (6).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100$$

Equation 4

Where True Positive Rate (TP) is the probability of authorized users that are recognized correctly over the total number tested, True negative rate (TN) is the probability of authorized users that are not recognized over the total number tested. False positive rate (FP) describes the percentage of unauthorized users that are recognized to the total number tested. False negative rate (FN) describes the percentage of unauthorized users that are not recognized falsely to the total number tested.

As can be seen from Table 3, the proposed fingerprint recognition using CNN with dropout method [56] leads to a significant performance improvement on real database.

Table 3: The training set result of proposed fingerprint recognition using CNN.

Images	Train set without dropout		Training set with dropout	
	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)
Original FP	98.96	3.65	99.31	2.35
Enhanced FP	99.49	1.93	99.56	1.23
Proposed Enhanced FP	99.13	2.16	99.63	1.17

Notably, the dropout technique yielded the greatest improvement in accuracy for both the training and test sets across four datasets. Furthermore, utilizing the dropout method resulted in the lowest loss, especially for the database being employed. For training set, it can be noted from Table 4 that the accuracy of 99.13% is augmented to 99.63% and the lost rate of 2.16% is reduced to 1.17% in the proposed method due to add the drop function in our system. For test set, based on the results yielded in Table 4, the accuracy of 99.33% is augmented to 99.48% and the lost rate of 2.16% to 2.03% in the proposed fingerprint identification method.

Table 4: The test set result of proposed fingerprint recognition using CNN.

Images	Test set without dropout		Test set with dropout	
	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)
Original FP	97.06	9.12	97.66	5.71
Enhanced FP	98.29	5.68	99.16	3.14
Proposed Enhanced FP	99.33	2.16	99.48	2.03

From Table 5, to demonstrate the superiority of the proposed fingerprint system, we tested its performance using different classifiers, including SVM, LR, RF, and CNN. Our findings indicate that the Softmax classifier achieved the highest accuracy of 99.48%, outperforming the other classifiers.

Table 5: The result of proposed system recognition biometric using CNN with different classifiers.

Classifiers	Fingerprint
CNN & SoftMax	99.48%
CNN & SVM	97.65%
CNN & LR	85.61%
CNN & RF	97.33%

Finally, we can conclude from these results that the proposed system is superior to other methods because:

1. The enhanced fingerprint patterns proposed in this study are noticeably distinct and more prominent compared to other enhanced versions. As a result, the proposed methods are highly likely to achieve a high identification rate.
2. The use of the dropout method results in better recognition accuracy compared to using only the dataset method.
3. Typically, using the CNN approach leads to better performance compared to combining different processes such as windowing and feature extraction. Therefore, a biometric recognition system based on CNN technique can outperform other classical and complex techniques.
4. Compared to current biometric systems, the proposed algorithm provides improved accuracy in identifying individuals and enhanced security for their information and data.

IV. CONCLUSION

This study presents a biometric identification system for attendance monitoring that utilizes fingerprint recognition based on Convolutional Neural Network. The experimental results, obtained from real databases, demonstrate that the overall performance of the proposed system, which incorporates CNN and different classifiers, outperforms the artificially pre-defined traditional fingerprint biometric systems in terms of identification accuracy. Based on the results, it can be inferred that the pre-processing algorithm has a positive impact on the accuracy of the proposed system. The dropout technique significantly contributes to increasing recognition accuracy by reducing the system's loss rate. For future research, extending the proposed algorithm to other applications would be worthwhile, and testing it on a more challenging dataset with a larger number of subjects should be considered.

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