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A Novel Approach to Fingerprint Authentication using Histogram Oriented Gradients for Feature Extraction and Machine Learning Convolution Neural Network for Classification

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Abstract

With applied biometrics, it is possible to identify a person by examining a feature vector of attributes derived from their physical and behavior characteristics. In biometrics, fingerprints have become one of the most famous and well known techniques of identification and authentication. In light of technological advancements and safety, fingerprint recognition has been successfully used in a variety of Civil, Defence, and Commercial applications for more than a decade. The use of fingerprints for signature applications started in the second millennium and studies have been conducted on the different aspects as well as attributes of fingerprints over the past decade. In addition to CNN for deep learning, this study introduces a Histogram Oriented Gradient for feature extraction. Histogram equalisation, filter enhancement, and fingerprint thinning are a few of the preprocessing strategies for obtaining fingerprint features. A deep convolutional neural network algorithm has been created for the purpose of classifying preprocessed fingerprints. Compared to deep learning networks, HOG-based CNNs is extremely efficient. In addition, CNN is challenged by its inability to rotate. Despite the fact that CNN has already been investigated, We propose a novel and simple HOG-based CNN that generates highly valued data efficacy and is rotation-invariant. For validation within the database, 64 epochs achieved 99.47% accuracy, against 100% training accuracy. A validation accuracy of 4.33% was achieved for an outside database with a training accuracy of 6.33%. In comparison with contemporary machine learning algorithms, the accuracy achieved in this work is considerably higher.

Keywords: Feature extraction, histogram oriented gradient (HOG), convolution neural network (CNN), machine learning.

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INTRODUCTION

In Biometrics, It is physical or behavioral characteristics that determine the identity of an individual [1]. Growing security concerns have led to an escalation in the complexity and severity of threats. In order to protect themselves against the effects of extortion and personality issues, educational institutions, organizations, Government agencies, and political agencies need protective shields. Whenever a new threat emerges, biometrics can prevent illegal access to vital information systems. Regularly implementing and updating security programmers is an essential part of every organization's operation, Our daily lives now include a progressively greater proportion of the use of biometric identification [2].

Having a trustworthy and secure method of authenticating individuals becomes more important in a range of facets of our life in the era of increased personal security. Individuals can be identified more easily with the use of biometric technologies. These methods allow a client to demonstrate ownership of a certain trademark. The uniqueness and richness of biometrics have made it an undeniable part of human life. With the biometric highlights in mind, it becomes clear that each person needs a different strategy and system for identifying and controlling themselves. Given the biometric highlights, it is obvious that each individual must be evaluated according to a number of physical characteristics based on the biometric highlights. Individuals are electronically identified via biometric identification systems [3].

A biometric system consists of various physical characteristics and physical elements. The evidence collected in the digital age is diverse, and includes fingerprints, signatures, keystrokes, voice recordings, ear recordings, and DNA samples.

Due to advances in biometrics, security systems for personal checks are being given a greater emphasis. Technology and safety are taken into account when providing biometric services, The use of biometrics is often necessary to keep data secure.

Fingerprint attributes are widely acknowledged as extremely pragmatic tools in the field of image processing and computer vision [4]. Biometric technology refers to the use of various physical attributes of our bodies for digital authentication [5]. This technology encompasses several physical components and distinct characteristics, including digital signatures, facial recognition, and DNA analysis. With biometrics in mind,security systems are being planned with more consideration for personal checking [6]. The distribution of biometrics serves two primary purposes: technical functionality and security requirements. Biometrics play a crucial role in ensuring data safety on a daily basis [7, 8].

Fingerprint recognition stands as one of the most well-known and highly robust biometric methods. Each fingerprint impression is entirely unique, belonging to only one individual and remaining constant throughout their entire life. In addition, with time, fingerprint recognition equipment and programming have become significantly more affordable [9]. Fingerprints are considered one of the most enduring and reliable means of identifying criminals and deceitful individuals. To prepare fingerprints for accurate analysis, pre-processing is necessary to eliminate disturbances, dryness, finger wetness, and variations in pressure. This pre-processing involves a multi-step procedure [10], including Smoothening filtering, Intensity standardization, orientation region estimation, Fingerprint segmentation, Ridge Extraction, and Thinning, which are distinct methods used in the process. Feature extraction plays a vital role in human identification. It is obvious that each person needs an secure authentication. The proposed system utilizes a novel feature extraction technique known as the Oriented Gradients Histogram algorithm.

Besides speech recognition and computer vision, Deep convolutional neural networks are used in many areas. Without having to make numerous human design decisions, It is possible to learn models of extreme complexity and breadth via these networks. These systems require a large training set, Neuralnetworks have various applications. However, without a big training set, it is challenging to extract enough information to optimise the parameters. Several attempts have been made in recent years to speed up CNN by decreasing the number of parameters. However these methods are successful in reducing the number of parameters while maintaining the effectiveness and accuracy of the trained model. In spite of this, we continue to believe that making these large and complex models tolerant of smaller training sets remains a challenge. Training should be guided in a way that preserves the parameters during training, as this is one realistic way to achieve this.

The decision made by CNN was impacted by a number of factors. Namely, it analyzes network data in addition to storing it. The CNN's applications are still possible despite the loss of a few pieces of data from one location. CNN is an candidate for Deep Learning because of its fault tolerance, parallel processing,and capacity to handle small datasets [11]. Despite their antiquity, CNNs were the best choice for our investigation for the reasons stated above.

Database of Biometrics

It is possible to make databases with separate images of the same person since specific databasesare readily available in the cyber world. The proposed work makes use of the FVC 2006 Database. Sweeping sensors are the form of sensors deployed. Criteria have been defined based on four distinct datasets provided by the organizers, namely DB1, DB2, DB3, and DB4. Owing to the fact that each database has 150 fingers with a finger depth of 12 samples That is, each database consists of 1800 images, and each of these databases will be divided into two subsets, labeled as A and B.

Contribution

An architecture for fingerprint recognition is proposed that employs Deep Convolutional Neural Network for classification, before that HOG for fingerprint preprocessing is postulated. According to the findings, the suggested method had a accuracy of validation as 99.47% against the accuracy of training 100%.

Organization

An overview of the survey can be found in "*Literature Survey*", "*Model*" presents the suggested model, along with further explanations and information about the data set, while "*Algorithm*" outlines the algorithm, "*Assessment and Experimental Results*" explores the research and its implications, Future studies are reviewed and recommended at *"Conclusion*", References are listed at "*References*".

LITERATURE SURVEY

Pradeep N.R and Ravi J [12], presents a method for accurate fingerprint recognition using Histogram Oriented Gradient. In terms of fingerprint recognition, HOG descriptor is thought to contain significant properties that achieve an average accuracy rate of 100%.

Vinod Kumar, et. al., [13] presents a novel image-based algorithm to record fingerprint local and global details and alleviate the shortcomings of minutiae-based fingerprint identification. 50 fingerprints are captured by a fingerprint scanner at 300 dpi, with 15 fingerprint images per person. The paper employs a matching algorithm, such as SVM, as a classifier. In comparison to the other two methods, the HOG-based approach demonstrated superior results. Jitendra P Chaudhari, et. al., [14] developed an algorithm that integrates the optimum combination of SVMs and Histogram gradients (HOG). The precision of the proposed algorithm is evaluated and compared with the accuracy of another model. The results of the testing and comparative data analyses indicate that the proposed algorithm exhibits a high level of consistency, achieving an accuracy of 96.36%.

In the study conducted by Sree Lakshmi K J et al. [15], a Human Identification method based on the Oriented Gradient Histogram is proposed. This approach is used to capture different blood vessel orientations in the sclera region, enabling efficient sclera recognition. Test results demonstrate that sclera recognition in the visible wavelength achieves high accuracy. On the other hand, Mostafa A Ahmad et al. [16] present a reliable multibiometric model that combines the histogram of oriented gradients with face and digital signatures for accurate identification of individuals. The methodology incorporates several parameters, including HOG feature weights and a matching distance method, to enhance accuracy. The results indicate that the HOG descriptor performs remarkably well, achieving an average accuracy of 100 percent.

Himabindu Sathyaveti et al. [17] introduces a static approach that merges various techniques to enhance fingerprint recognition. This approach combines Speed up Robust Features (SURF), Low level gradient features, pyramid extension of the Oriented Gradient Histogram (PHOG), and Principle

Component Analysis (PCA). The goal is to address issues with dynamic software approaches that demand user coordination and longer computation time.

The proposed method focuses on extracting fingerprint image features from a single fingerprint image, eliminating the need for complex user interactions. To classify fingerprint matches between genuine and fake fingerprints, the authors employ the best Support Vector Machine (SVM) classification technique.

An innovative framework for protecting sensitive data usingfingerprints was developed by Daesung Moon, et. al., [18]. Decoding is performed using the algorithms Geometric Hashing and RS. In Anil Jain, et. al., [19] an online fingerprint identification scheme has been developed and put together, Minutia extraction and minutia matching are conducted simultaneously. There is a comprehensive matching elastic alignment algorithm proposed. By using this technique, nonlinear deformations and inaccurate transformations between fingerprints can be compensated for.

The methods proposed by Shlomo Greenberg et. al., [20] for fingerprint image enhancement have two distinct advantages. The first step employs image binarization, Wiener filtering, and histogram equalisation. For the second method, one filter is applied for direct grayscale improvement. The handheld devices designed by Seifedine Kadry and Aziz Barbar [21] consist of a technique for addressing the mobile communication authenticity problem. It is against any falsification by another user.

Tabassam Nawaz, et. al., [22] has suggested a system to keep records and attendance throughout the entire process. Computer records are stored on a server that receives attendance data from a sensor. To decompose fingerprint-oriented patterns into two parts, Michael Kaas and A. Witkin [23] have discussed them. In the coordinates system, the residual pattern is found by describing the image along with the field flow describing the anisotropy.

Methods for estimating a high resolution directional field from fingerprints were proposed by Asker M. Bazen and Gerez [24]. The singular points are detected by the directional field, and the point orientations are calculated.

Lin Hong, et. al., [25] created a unique approach for dividing thefingerprint image into a collection of filtered images. To distinguish recoverable from unrecoverable regions in the input image, an orientation field and a quality mask are calculated. An adaptive improvement of the fingerprint image is made using theestimated orientation field in recoverable regions.

Using a CNN four-layer and comparing the distance of Euclidean, Radzi, et. the authors in [26] successfully extracted the features. Convolutional neural network suggested by C. Xie and A. Kumar [27] is one of the most current deep neural network techniques. Qin and El-Yacoubi [28], suggested an advancedrepresentative feature extraction technique. Foreground and background images were first segmented to create the segmentation image for the foreground. CNN is used to predict whether a particular foreground pixel is a non-vein point or a vein point. As a final step, a completely convoluted neural network was used to reconstruct the missing vein design in the segmented image.

Problem Identification

Survey results reveals that majority of conventional algorithms for matching fingerprints donot correctly evaluate or categorize themselves, do not handle partial input, do not preserve feature information, and cannot do multiple calculations simultaneously. As CNNs are capable of processing complex computations quickly, they have attracted researchers.

MODEL

Methods to extract features, Indicators of performance, models, datasets, and classifiers are all covered in this section.

Definitions

False Acceptance Rate (FAR)

Eq.1 illustrates a biometric safety system that accepts incorrectly an access attempt made by an unauthorized user.

$$(FAR) = \frac{\text{No. of unauthorised persons accepted by the system}}{\text{Total No. of persons out of database}} \quad (1)$$

False Rejection Rate (FRR)

Eq. 2 illustrates an issue with a biometric safety measurement system that incorrectly refuses a licensed utilize the right of entry.

$$(FRR) = \frac{\text{No. of authorised persons rejected by the system}}{\text{Total No. of persons in the database}} \quad (2)$$

Total Success Rate (TSR)

Based on Eq. 3, the likelihoodof various images from one person being matched correctly.

$$(TSR) = \frac{\text{No. of right persons matched}}{\text{Total No. of persons in the database}} \quad (3)$$

Equal Error Rate (EER)

The rate at which rejection error is same as acceptance error.

$$\boldsymbol{EER} = \boldsymbol{FAR} = \boldsymbol{FRR} \quad (4)$$

Threshold

A distance formula is employed to calculate the Error Vector (EV), which measures the distance between the test image and the database image. The average of the Error Vector (EV) serves as the recognition threshold value.

Training

These are introduced to the network during preparation, and the network is updated to fix its errors.

Validation

A network generalization assessment is used to halt training when generalization has failed to improve.

Epochs

An epoch is a period of time marked by certain changes, it is defined as one loop over the complete training dataset.

Recommended Model

The block diagram for the suggested approach, which makes useof HOG based features to more accurately identify a person followed by CNN classification is shown in Figure 1.

HOG based Feature Extractor

Object recognition and object identification using HOG capabilities are commonly used in computer vision applications. The core principle of this technique is that the existence and shape of a local entity can always be precisely represented by intensity gradients or boundary distribution.

The following steps were taken in determining the HOG features:

Step 1

Read the input Fingerprint Image.

The input image resolution will be 96x96 pixels. bmp format.

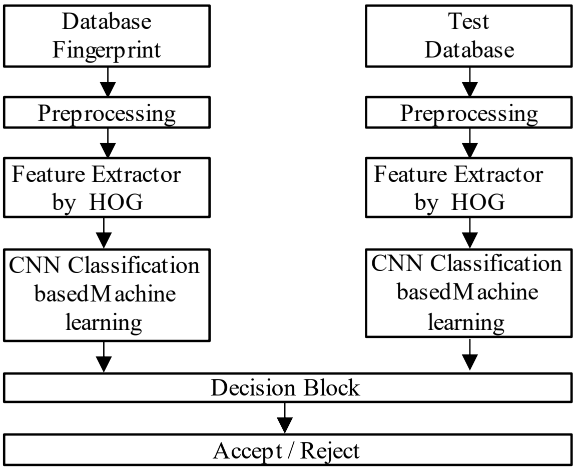

Figure 1. CNN classification by machine learning using feature extractors based on HOG.

Step 2

Gradient Computing.

A Gradient values are calculated using a different derivative mask for vertical and horizontal points in 1D. The grayscale image is filtered with filter kernels using this approach.

$$D_x = [-1\ 0\ 1] \text{ and } D_y = [-1\ 0\ 1]' \tag{5}$$

Hence, by using a convolution operation, we determine the x andy derivatives of an image I:

$$I_x = I * D_x \text{ and } I_y = I * D_y \tag{6}$$

Using this equation, we can determine the magnitude of Gradient:

$$|G| = (I_x^2 + I_y^2)^{0.5} \tag{7}$$

and the Gradient of Orientation can be seen as follows :

$$\theta = \tan^{-1}(I_y/I_x) \tag{8}$$

Step 3

Histogram block and generation offeature vector.

Following the gradient calculation, the subsequent step involves generating histograms of cells. Based on the values of each pixel, a weighted vote is cast in the orientation histogram channel. The rectangular cells are uniformly distributed, and their histogram channels correspond to different orientations while using an "unsigned" gradient. In terms of vote weighting, each pixel can contribute its gradient magnitude, the square root of the gradient magnitude, or the square of the gradient magnitude, depending on the specific weight of the vote and the gradient magnitude. Changing contrast and illumination require normalizing gradient strengths locally. As the next step, cells are combined or grouped into larger blocks whose spatial interconnections are interconnected.

Feature lengths of normalized cell histograms are computedfrom HOG vectors for all block regions.

Step 4

Classification

A fingerprint is matched by determining its Euclidean distance from its corresponding vector. By utilizing this minimum score, the two fingerprints can be compared to identify the most suitable match. A concise depiction of HOG's fingerprint is presented in Figure 2.

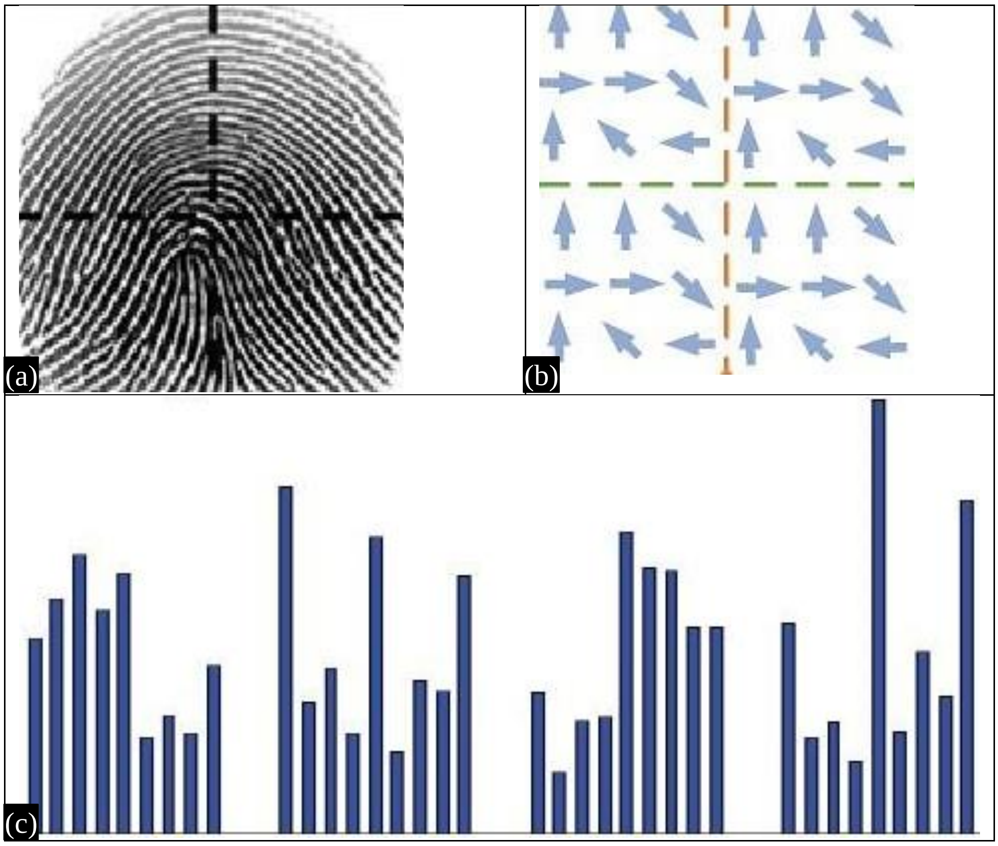

Figure 2. HOG Pattern of Fingerprint (a) Divided into Fingerprint Images of 4 Blocks (b) Gradient Orientation ofEach Block (c) Gradient Oriented Histogram.

CNN Classification

As a component of modern fingerprint recognition architecture, this paper suggests the following architecture. The classification task is carried out using Deep Convolutional Neural Networks. The suggested architecture is illustrated in Figure 3, An Thermal fingerprint scanners were used to scan user fingerprints, and the generated data were used to create a dataset for the experiment. An image was orientated, improved, pores were detected, and the ROI was selected as part of preprocessing. A fingerprint ROI of 480×320 pixels results from the above steps.

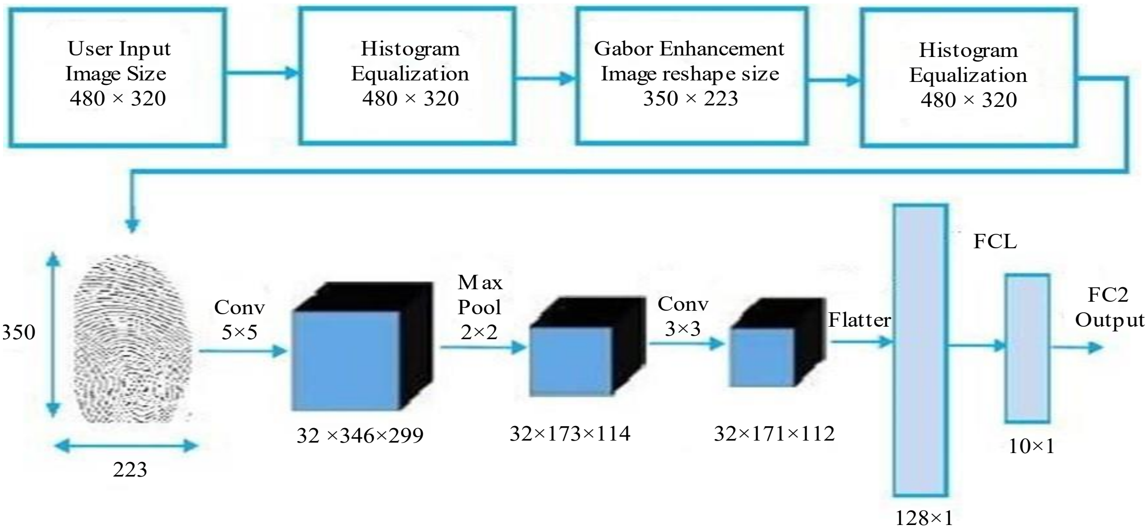

Figure 3. CNN Architecture Proposed.

Matching

An estimate of the distance of Euclidean between noteworthy feature vectors is used to create the matching fingerprint.

$$d(x,y) = d(y,x) = \sqrt{(x_1 - y_1)^{2+} \qquad + (x_n - y_n)^2} \tag{9}$$

where 'y' = Features of image Database and 'x' = Features ofTest image.

When the Euclidean distances between two vectors are smaller than a predefined threshold, it is concluded that "the two images belong to the same finger." However, if the Euclidean distances exceed the threshold, the decision is made that "the two images come from different fingers."

ALGORITHM

The effective identification of individuals can be achieved by combining the HOG-based feature extractor with a CNN classifier as shown in Table 1.

Table 1. An algorithm for fingerprint recognition using hog based feature extractor and CNN classifier.

Input	**Fingerprint Image**
Output	Indication of an individual's identity.
Step 1	Fingerprint from database is used to obtain theimage.
Step 2	Resizing the image to $2^x \times 2^y$ dimension.
Step 3	Extraction of features utilizing the HOG algorithm
Step 4	Read the input Fingerprint Image, Input image Resolution will be 96×96 with .bmp format.
Step 5	Gradient Computation, For each pixel I(x,y), calculate the magnitude of the gradient byEq.(7) and orientation by Eq.(8)
Step 6	Block Histogram and Feature Vector Generation.
Step 7	The final feature vectors are generated by combining all Histograms from each block.
Step 8	Implementation of CNN Classifier
Step 9	A test image is created by repeating steps 1 to 8.
Step 10	A Euclidean threshold value confirms the image.

ASSESSMENT AND EXPERIMENTALRESULTS

HOG Results

Measured by FAR, FRR and EERcomputing.

For Experimentation

Our experiment included the first 140 persons in FVC DB3-A, each of whom had 12 fingerprints.

For Training

For training, first 40 persons containing first6 fingerprint images per person are used, hence total images for training used are 240 images.

For FRR Calculation

For FRR calculation, 7^{th} Image is considered from first 40 persons (Inside Database).

For FAR Calculation

For FAR calculation, 1st Image is considered from images from 50-80 persons (Outside Database).

As shown in Table 2, if the threshold is varied from 0.25 to 0.50,the FRR is decreased from 100% to 0%, whereas if the threshold is varied from 0.35 to 0.65, it is increased from 0% to 100%, andthe EER is 39%. Observation of the threshold value at 0.43 indicates that FRR and FAR coincide, and this value is deemedas optimal threshold value.

Table 2. Fluctuations of FRR and far above and belowthe threshold for FVC 2006 DB 3_A.

Threshold	FRR	FAR	TSR
0	100	0	0
0.05	100	0	0
0.10	100	0	0
0.15	100	0	0
0.20	100	0	0
0.25	100	0	0
0.30	95	0	5
0.35	82.5	0	17.5
0.40	60	19.35	40
0.45	15	61.29	85
0.50	0	90.32	100
0.55	0	96.77	100
0.60	0	96.77	100
0.65	0	100	100

CNN Experimental Results

Training accuracy and validation accuracy measured against the number of epochs are its Metrics used to evaluate the results.

Recognition Accuracy (Inside Database)

Taking into consideration 1 image per person in the database,100 images will be created as shown in Table 3.

Table 3. Recognition Rate of CNN Model for Inside Database.

Training Accuracy	Validation Accuracy	Epochs
99.10	91.03	16
99.70	92.33	32
100	99.47	64

The proposed CNN model has been prototyped using Matlab. Asa result of loading the training and testing data sets into the models, different layers and parameters are employed. A CNN model's consistency and accuracy are affected by the size and number of kernels (filters) usage. The CNN-based model's accuracy has been checked over different epoch counts using a 5x5 kernel based on our observations. An 100% accuracy is obtained with 64 epochs, and with less epochs the accuracy does not change substantially. During model training, early stopping technique is used to prevent overfitting caused by too many epochs or underfitting caused by too few epochs.

The model training process is automatically stopped once no substantial performance change has been observed for a period of time.

Accuracy of Recognition (Outside Database)

With 50 people and one image per person, 50 images outside thedatabase make up the 50 images for 50 people as shown in Table 4.

Table 4. CNN model recognition rate with gaborfilter for outnside database.

Training Accuracy	Validation Accuracy	Epochs
4.1	3.66	16
5.22	4.11	32
6.33	4.33	64

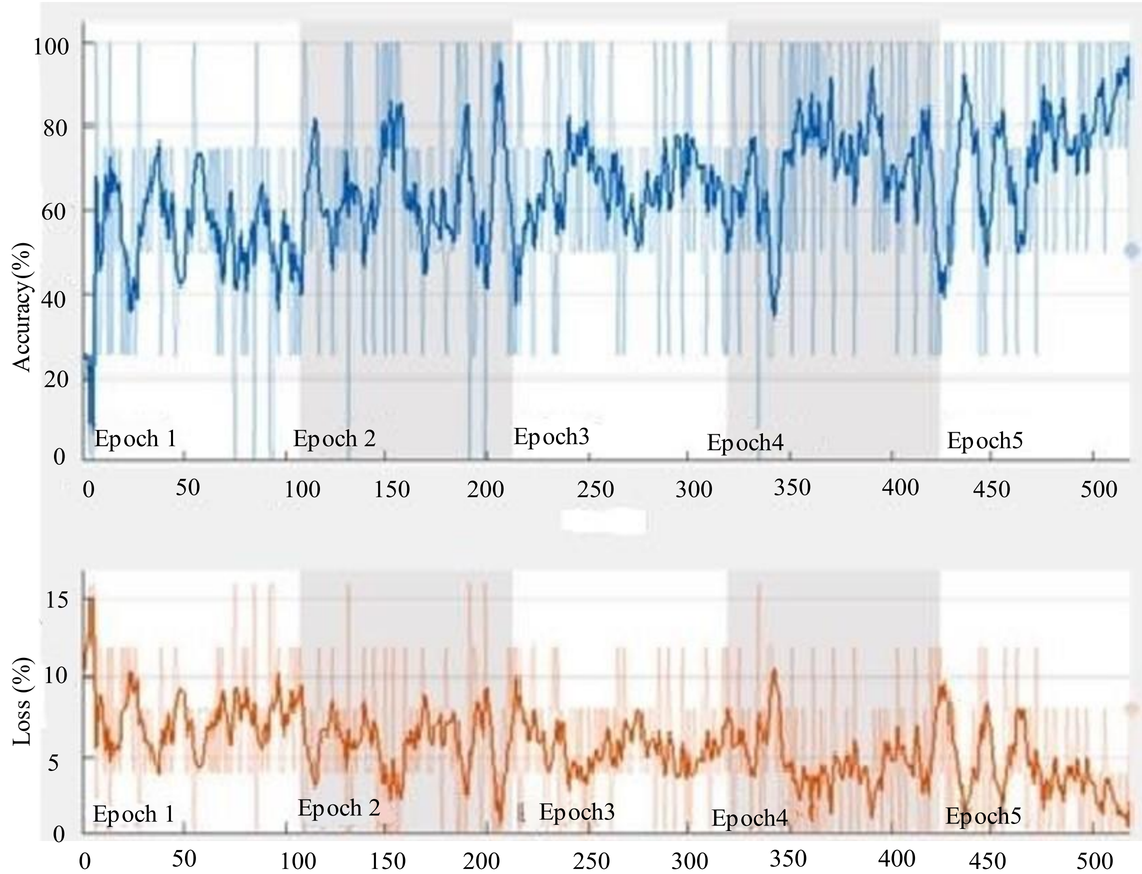

Figure 4. For the CNN architecture, accuracy and loss v/sepochs learning curve.

Figure 4, Displays Accuracy and Loss v/s Epochs for the CNN architecture. It is evident that accuracy gradually increases as thenumber of epochs increases and losses gradually decrease as the No. of epochs increases and no over fitting occurred during training and obtaining accuracy curves. Learning rates begin at 0.001 for minibatch sizes 16, 32, and 64. There were only smallamounts of loss values on the loss curve.

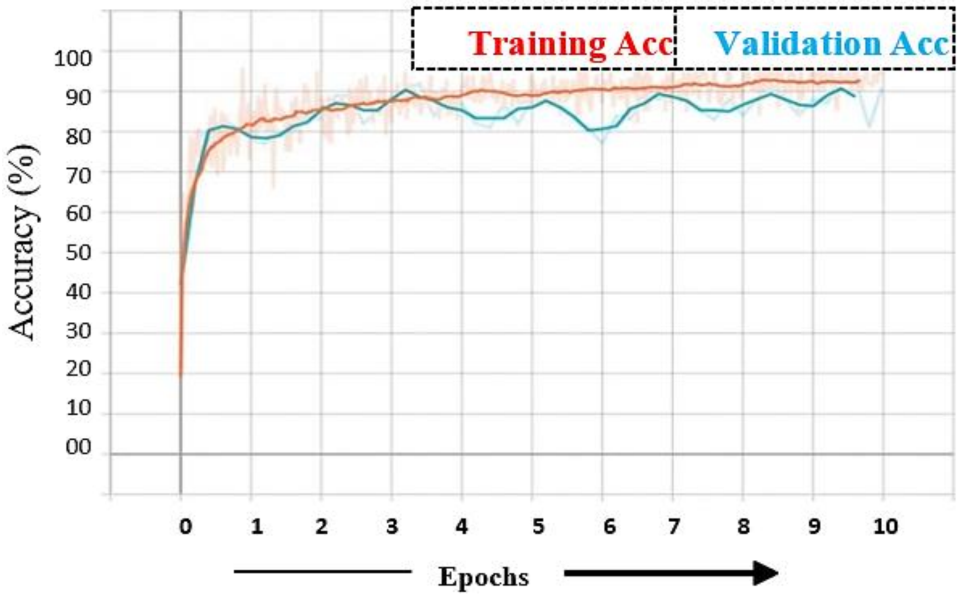

Figure 5. Training (Red) v/s Validation (Blue) accuracies.

From Figure 5, It is evident that validation accuracy follows training accuracy curve, and the model performs exceptionally well for 64 epochs to reach 99.47% validation accuracy.

A Comparison of Performance Between the ProposedHOG based CNN Algorithm and other Algorithms

It is more efficient to use HOG-based CNN models rather than traditional methods as shown in Table 5.

Table 5. Summarizes the performance algorithmagainst other existing algorithms.

Method	Features	Accuracy(%)
V A Bharadi, et. al., [29]	Hybrid Wavelets	77.00
M M H Ali, et. al., [30]	Minutia xtractor	80.03
Satish Kumar Chavan, et. al.,[31]	Gabor Coefficients	82.95
Yang J, et. al., [32]	ROIFE_CNN	95.10
Michelsanti D, et. al., [33]	CNN	96.01
Pushpalatha K N, et.al., [34]	Gabor Coefficients	96.30
Nguyen H T, et. al., [35]	Random Forest (RF) + CNN	96.75
Bhavesh Pandya, et. al., [36]	CNN basedGabor	98.21
Proposed HOG basedCNN model.	HOG & CNN	99.47

CONCLUSION

An easy-to-use, secure, and robust way of identifying and verifying individuals is fingerprint authentication. Based on HOG-based CNN Deep learning, the paper discusses fingerprint authentication using fingerprint images. FVC 2006 Database is used to validate the algorithm. It is possible to use patterns foundon body parts as passwords for biometric identification. We demonstrated a novel Deep Learning architecture for recognizing fingerprints that includes a pre-processing stage for extracting features based on HOGs before using the neural network. The findings suggest that CNN was the most effective of all the methods compared. The CNNs reject no fingerprints, but they are also more accurate than feature extractors with a certain rejection rate. As well as being extremely competitive, CNN's runtime is superior to most of the contemporary algorithms. It is intended to conduct training and testing using a larger data set in future work. To build more reliable biometric recognition systems, future research will incorporate multi modal data which combines attributes of fingerprint, iris, face, and keystroke features into deep learning architectures.

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