A Deep Learning based Approach for Biometric Recognition using Hybrid Features

Mrityunjay Kumar[1], Arvind Kumar Tiwari[2]
[1,2]*Department of CSE, Sultanpur(India)*

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Abstract: Biometric authentication and identification is most important and challenging problem in this evolved era of computer technology. Goal of new technical developments is to make our task easy and life smoother. It is important to develop an efficient computational method to recognize and identify biometrics more efficiently with least time delay. This paper proposed a CNN based multimodal biometric identification system using feature fusion of three biometric traits Faces, Fingerprints, and Iris. In this paper PCA and WT are used for feature extraction and feature fusion respectively. The accuracy of the proposed approach is about 96.67% on fused features of three biometric traits Faces, Fingerprints, and Iris. The proposed approach in this paper provides better accuracy in compare to the existing method in literature.

1 INTRODUCTION

Biometrics is the method of identifying an individual using physical or behavioral features of an individual like fingerprints, faces, gait, and voice etc. Base of biometrics systems exists in the permanence and uniqueness of the physiological and behavioral traits of individuals. The technological developments in the modern era are very fast. This fast developing era need more fast, secure and reliable identification systems in variety of requirements like Airports, International border crossings, Law enforcement agencies, Commercial places like banks and other business applications, availing benefits from government's social service schemes etc. Biometrics has capacity to handle large identity management systems and for this reason identification systems based on biometrics placed themselves in the position where no competitor exists. Though it is not completely a novel idea to use biometrics for identification, there are evidences for more than thousands years ago it was in use in some form but not exactly same or nearly same as it is in modern era. It is about 50 years ago when IBM first proposed that a remote computer system may use for the identification purpose of the human (Jain, 2007).

Evidences of biometrics are older than the centuries. In some ancient caves, there were some traces of claws in front of the artists who have been created about 31000 years ago, such as the modern painters used to prove their signature identity on their created paintings.There is also proofs regarding use of fingerprints for identifying individual's around 500 B.C. Business transactions in Babylonian civilization used clay tablets to record fingerprints (Maio, 2004).

Biometrics recognition is most popular tool for human identification and verification in modern era for so many reasons. Some of the obvious reasons are performance, reliability, real time computability, and security. General thinking about biometric traits are that they are unique and permanent. But in reality in spite of having sufficient amount of uniqueness the biometric systems are not sufficiently reliable in terms of permanence of human biometric traits, both behavioral as well as physiological. There are numerous researches which proven the degradability of common biometric traits. By this reason the identification/recognition process using biometrics becomes not to trusted fully. In most of the cases the Genuine Acceptance Rate(GAR) is not 100%, and it always also contains some False Acceptance Rate(FAR). So there is always a better model possible with respect to a existing

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identification/verification system using biometric recognition.

In the modern era traits like fingerprints, faces, iris, palm prints, hand geometry, DNA, voice samples etc. may be used for biometric authentication. A biometric recognition system using only single trait as identification/verification tool has a high frequency of failure because of the changing nature for the considered trait. For e.g. suppose we develop a system which uses fingerprint as a biometric trait for identification for a group of persons which include multiple job class persons (Some of them are might physical workers like labors etc). People who work in rugged conditions have high rate of change in their fingerprints, which will increase the failure rate of the system. Similarly systems based on Face and Iris may suffer from problems of their own.

Biometric traits may even used in various forms like in a way where only one trait is used for identification generally referred as uni-modal or any combination of two or more traits generally referred as multimodal of biometric identification. Systems using multiple biometric traits for identification are more reliable as compared to systems with single biometric traits. This is because suppose fingerprint of a person sufficiently changed due to his/her working conditions their face and iris will be there for the identification of the person. Similarly if there is any major change in face then there are fingerprints and iris are there for identification and so on. There are a number of reasons which makes a multimodal biometrics system more reliable, few of them are:

1. A result from obtained from combination of multiple traits is more acceptable than a single trait system.

2. If a person somehow lost his any trait then we are still capable of verifying his identity with the help of remaining traits in multimodal system.

3. A multimodal provides high security against forgery because spoofing becomes more difficult for a person entering to the system and claiming a registered identity.

This paper is about developing an identification system based on multimodal which used feature fusion technique. The traits which are used in this method are faces, fingerprints and iris. For the purpose of increasing efficiency of the system we used intra class variations by using five various poses of faces, five different fingerprints and two different images of each eye. Fig.1 presents a summary of proposed model.

This model used a deep learning based feature fusion technique for identification. More specifically it uses CNN of deep learning methods.

2 RELATED WORKS

Jain et al. (1996) described a two stage on line verification system based on fingerprints. The first stage is minutia extraction and the second one is minutia matching. It used a fast and reliable algorithm for feature minutia extraction, which results improvement in Ratha *et al.* algorithm and for minutia matching, they developed an elastic matching algorithm based on alignment. It directly correlates the stored template with the input image omitting the expansive search. It is also capable of dealing with the nonlinear deformations and inexact pose transformations between fingerprints. This method was very efficient in terms of reliability as well as time complexity. The average verification time is reduced up to about eight seconds using SPARC20 workstation (Jain, 1996).

Van der Putte et al.(2000) presented a paper which examines how biometrics systems based on fingerprints can be fooled. It categorizes the process in two categories which includes with the co-operation of fingerprint owner (In the cases of attendance monitoring systems) and without the co-operation of fingerprint owner(In the applications involving authentication purposes eg. PDS systems etc).It is possible to easily store the fingerprint sequences on smart cards and it is very much possible to read this smart card via a solid state fingerprint scanner. It categorizes the counterfeiting in two parts, first is duplication with Co-operation and second is duplication without Co-operation. In both the cases the duplicate image creation of fingerprint is possible. In the first case with the help of wafer thin silicon dummy is used to take samples of fingerprint and further used when required. In the second case it is possible always to make duplicate copies of finger prints with the help of some storage devices by associating it with scanner. It is also possible to collect samples of fingerprints from a surface by using stamp type materials (Van, 2000).

Liu et al. (2001) presented a paper on face recognition which combines shape and texture features which is Enhanced Fisher Classifier (EFC). Face geometry contains the shape while shape-free normalized images are provided by texture. Dimensions of shape and texture spaces are reduced by PCA and enhanced Fisher linear discriminant model is used enhancing generalization. The great benefit of the method is that it achieves accuracy of 98.5% and using just 25 features (Liu, 2001).

Blanz and Vetter (2003) presented a mechanism for face recognition, which is capable to work for varying poses and illuminations. Wide range of variations and varying illumination level requires to simulation of image formation in 3D space. For this simulation purpose computer graphics is used. Efficiency of the method is judged on three different views: front , side, and profile. The front view performed better than two other with a success rate of 95% , whether profile view is the lowest success rate with 89% (Blanz, 2003).

Daugman(2004) presented a study and observations on working of iris recognition and its performance. The author examined the problem of finding the eye portion in an image in briefly by developing concepts and appropriate equations. In the later phase of the paper the author presented a speed performance summary for various operations performed during the process in which XOR comparison of two Iris Codes takes minimum time which is 10 micro seconds while Demodulation and Iris Code creation takes a maximum of 102 mili seconds (Daugman, 2004).

Daugman(2006) presented a paper which examined the randomness and uniqueness if Iris Codes. The author of the paper had taken 200 billion Iris pairs for their comparison work. This paper is helpful in finding false matches in iris recognition for large database. Daugman developed his own algorithm for the purpose named Daugman Algorithm and it is found that over 1 million comparisons there is a maximum of 1 false match occurred (Daugman, 2006).

(Shams et.al. 2016) presented an experimental work for biometric identification which used a multimodal based on Face, Iris, and Fingerprints. This experimental work used SDUMLA-hmt database, where data is present in the form of images. The images are preprocessed by using Canny edge detection and Hough Circular Transform. Further, they used Local Binary Pattern with Variance(LBPV) histograms for feature extraction. Separately extracted features are fused together. Feature reduction is accomplished by LBPV histograms. Combined Learning Vector quantization classifier is used for classification and matching purpose. The system was able to achieve GAR 99.50% with minimum elapsed time 24 Seconds (Shams, 2016).

(Choi et.al. 2015) presented a multimodal biometric authentication system based on face and gesture. Gesture is represented by various frames from one pose to another. This work is capable of accepting faces and gestures from moving videos. HOG descriptor is used for representation of gesture. 4-Fold Cross Validation is used for validation in this work. The performance of the system is about 97.59% -99.36% for multimodal using face and gesture. The whole work is performed on a self made database of 80 videos from 20 different objects (Choi, 2015).

(Khoo et.al. 2018) presented a multimodal biometric system based on iris and fingerprints which uses feature level fusion for modal development. Indexing-First-One (IFO) hashing and integer value mapping is used for the purpose. CASIA-V3 Iris database and FVC 2002 fingerprint database is used in model development. The main reason behind use of IFO hash function is its capacity survival against many attacks methods like SHA and ARM. The equal error rate (EER) of the system is provided in the paper which is 0.3842 for Iris, 0.9308 for Fingerprints and 0.8 for IFO hash function. There is no description provided about elapsed time (Khoo, 2018).

(Ammour et.al. 2017) presented a paper for biometric identification based on face and iris. Face recognition is performed by three methods discrete cosine transform (DCT), PCA and PCA in DCT, and Iris recognition is also performed by three methods which are Hough, Snake and distance regularized level set (DRLS). They used ORL and CASIA-V3-Interval dataset for their experimental work. Fusion is applied at matching score level in this work. Face recognition results with PCA is 91%, with DCT is 94% and with PCA in DCT is 93% with recognition times 0.055s, 2.623s and 3.012s respectively. Iris recognition results with Hough are 81%, with Snake is 87% and with DRLS is 80% with recognition time 15.82s, 15.78s, and 16.52s respectively. In the multimodal the recognition rate of Z-score normalization is maximum and it is 98% (Ammour, 2017).

(Parkavi et.al. 2017) presented a biometric identification system based on two traits fingerprint and iris. Separate templates of fingerprints and iris are obtained by minutiae matching and edge detection. Decision level score fusion is applied for decision making. They are able achieve accuracy of 97%, but the size of dataset and time complexity is mentioned nowhere (Parkavi, 2017).

(Sultana et.al. 2017) presented a multimodal biometrics system based on face, fingerprint and a very rare trait social behavior. The social behavioral trait is obtained by a social network and combined with traditional traits faces and fingerprints. The social behavioral data is obtained by various social media platforms a user is associated with. The key idea is that two people having similar social behavior profile has very less chance of similarity of face and ear and vice- versa. The model performance accuracy is about 92%, while time complexity related aspects have not been discussed (Sultana, 2017).

(Gunasekran et.al. 2019**)** presented a multimodal biometrics recognition using deep learning approach for traits like faces, fingerprints and iris. Images are taken from CASIA dataset. Contourlet transform is used for preprocessing of images. Histograms are obtained and weighted rank level fusion is applied for combining the key features. Deep learning is applied for matching. It achieved up to 96% of accuracy when dataset size reaches to 500. The best thing is that they achieved time in milliseconds. The maximum time it took was 49.2 milliseconds. The key outcome of this work is that, deep learning based approach performs better with increasing size of dataset, while time complexity increased very slightly (Gunasekran, 2019).

(Cheniti et.al. 2017) presented a multimodal biometric system using face and fingerprint using symmetric sum-based biometric score fusion. Score level fusion is tested on two different partitions of NIST-BSSR1 database, which are NIST-Multimodal database and NIST-Fingerprint database. GAR of 99.8% is obtained by S-sum generated by Schweizer & Sklar t-norm (Cheniti, 2017).

(Zhang et.al. 2017) proposed a multi-task and multivariate model for biometric recognition using low rank and joint sparse representations. This experimental work used three different datasets, WVU, UMDAA-01, and Pascal-Sentence in non-weighted and weighted categories. This work is based on multiple traits and traits are not specialized. They used different combinations of biometric traits from different datasets, like fingerprint, iris and faces. The modal performed variably for different datasets and variance is about 18% with changing datasets. Its recognition rate is 99.80% for both non-weighted and weighted categories in WVU dataset, for UMDAA-01 dataset its performance is 89.51% and 90.45% for non-weighted and weighted respectively, for Pascal-Sentence dataset the recognition rates are 81.48% and 82.72% for non-weighted and weighted respectively (Zhang, 2017).

3 PROPOSED WORK

A deep learning based approach which uses CNN for the multimodal biometric identification using feature fusion is presented in this section. Using deep learning on feature fused images of multiple traits is a good idea. The method uses PCA for feature extraction, inverse wavelet transform for feature fusion and CNN for classification and matching. The biometric traits which are used in the work are faces, fingerprints, and iris of SDUMLA-HMT database (Yin, 2011). The proposed work is an integration of a series of works like preprocessing, feature extraction, feature fusion, training and testing, and decision making. A general overview is presented in the Fig.1 and a corresponding flow chart is presented in Fig.2.

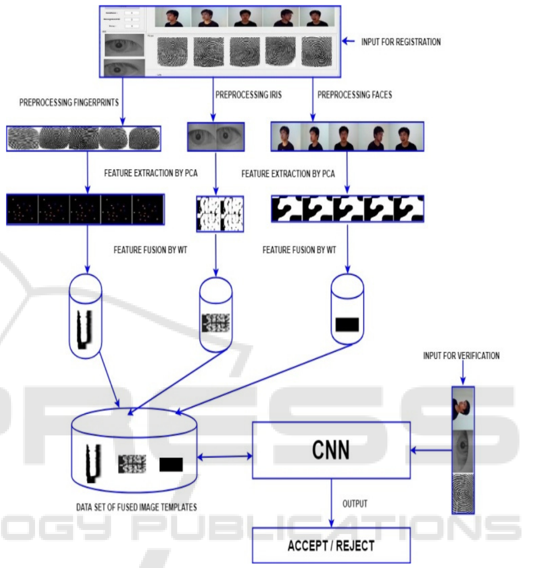

Figure 1: An overview of proposed Mode

3.1 Preprocessing

The images obtained from sensors are not directly operable for so many reasons. The primary task is to identify the desired portion of the image on which operation can be performed. The preprocessing generally includes localization, segmentation and normalization. The objective of the various operations is detection of interested parts, finding the patterns in images and to resize all the images to uniform size so that similar operations are performed easily. The resizing is necessary when we have samples from various input devices, because the image which contains the extracted features may vary in size due to a variation in size of input images and this cause the problem in matching. General tasks involved in preprocessing are depicted in Fig.3.

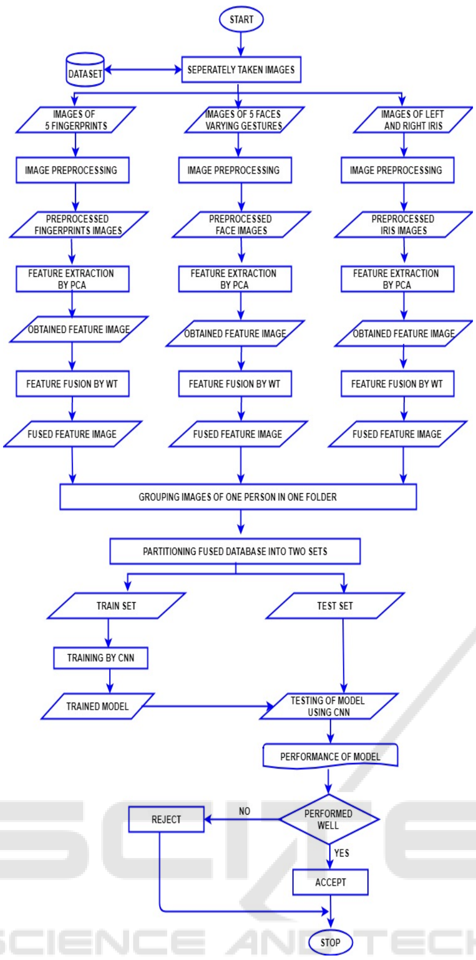

Figure 2: A flow chart of proposed Model

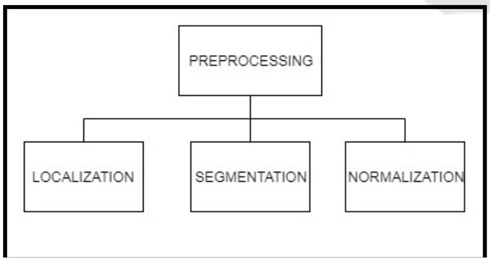

Figure 3: General tasks involved in Pre-processing

3.1.1 Fingerprints

RGB to Gray is applied to input finger images, if the input image is a colored image. If input image is a black and white image, then this operation is not required at all. Mask operation is applied to image to display meaningful area of image. Mask basically provides our desired blocks of the image on which further operations is to be performed. The result of masking is shown in the Fig.4.

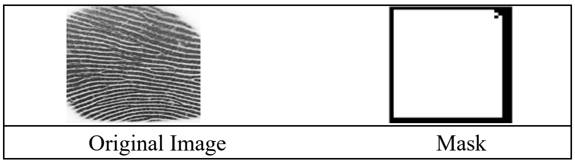

Figure 4: Result of Masking on a Fingerprint Image

3.1.2 Faces

The desired area is detected by Viola Jones algorithm of the input face image. The key principle of using Viola Jones algorithm is that it is capable of detecting faces in a sub window of the input image, while the standard face detection algorithm always try to detect faces from the whole input image which is time consuming. RGB to Gray is applied to the cropped image for eliminating the hue and saturation information while persisting luminance. Effects of preprocessing on face images are depicted in Fig. 5.

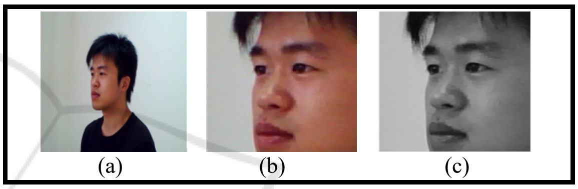

Figure 5: Effect of pre-processing on Face Images (a) Original Image (b) Localized Image, (c) RGB to Gray Image

3.1.3 Iris

RGB to Gray is applied to the input iris images if they are color images. In case of a black and white iris input images this operation is not required at all. Black hole search is used to localize the portion of iris image which is desired. Masking operation is performed to spot pupil inside iris image. Operation of normalization is performed to increase the intensity of the pixels present in spotted area. Effect of pre-processing on Iris Images is depicted in Fig.6.

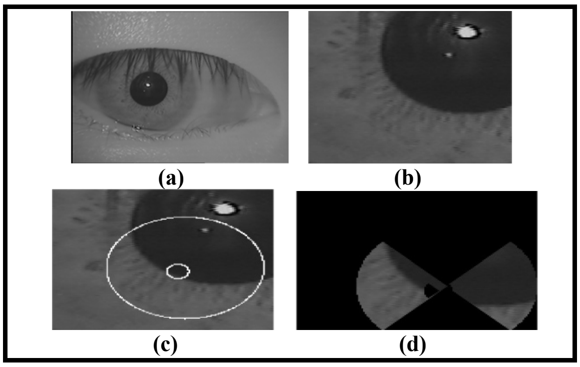

Figure 6: Effect of pre-processing on Iris Images (a) Original Image, (b) Localization, (c) Masking, (d) Normalization

3.2 Feature Extraction

After pre-processing, Principal Component Analysis (PCA) is applied on the obtained images for feature extraction. PCA is used because of its simplicity and performance. It finds new and small set of variable while retaining the original ones. It is a statistical method.

Any large data set consists many variables which are interrelated to each other in some way, thus the dimensionality of the data set is very high. Dimensionality of the data set is reduced by PCA, while retaining highest degree of variance as possible. Once we have a reduced dimensionality with maximum variance, it is possible to retain the original motive of the data set. The goal is achieved by transforming to a new set of variables, referred as principal components. These obtained variables are uncorrelated and organized in a way that some of them retain most of the variation present in all of the original variables.

Suppose we have a set of **n** random variables and **v** is a vector of it. If **n** is very large then it is not feasible to analyze **n** variances and **1/2(n(n-1)** covariance. Then it is wise to look for a new set of variables which contains less than **n** elements and which contains most of the variance represented by the original set.

To achieve this we have to look first a linear function $\mathbf{f_1'(v)}$ of the vector **v**, which contain the maximum variance, where $\mathbf{f_1}$ is a vector **n** constants

$\mathbf{f_{11}}$, $\mathbf{f_{12}}$, ... $\mathbf{f_{1n}}$ and $'$ denotes the transpose, i.e

$$\mathbf{f'(v) = f_{11}v_1 + f_{12}v_2 + \dots\dots\dots + f_{1n}v_n}$$

Continuing this we look for a linear function $\mathbf{f_2'(v)}$, which is not related to $\mathbf{f_1'(v)}$, with maximum variance and so on. By this way at the $\mathbf{k^{th}}$ stage a linear function $\mathbf{f_k'(v)}$ is obtained which contained maximum variance. $\mathbf{f_k'(v)}$ is the $\mathbf{k^{th}}$ principal component . We have to iterate this up to **n** principal components, but in general it is observed that we have to never reach up to **n.** Most of the variance in **v** is obtained for **i** principal components, where $\mathbf{i \leq n}$ (Jolliffe, 2003)(Takane, 2016)(Sanguansat, 2012).

3.2.1 Fingerprint

Feature extraction from fingerprint includes location of minutiae points in the input image. The operation is shown in the Fig.7 (a) .Once minutia points are located we just store only those minutiae points ignoring all other points from the image. A resultant feature image is depicted in Fig. 7 (c).

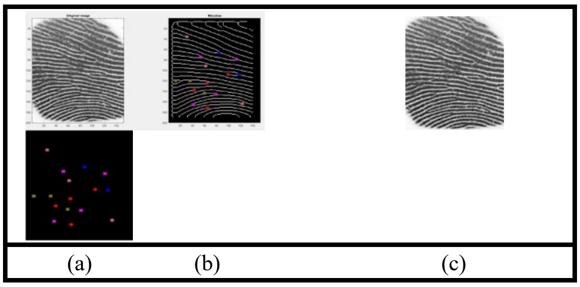

Figure 7: Feature Extraction From Fingerprints (a) Detection of Minutiae Points, (b) Original Image, (c) Bifurcation Points

3.2.2 Faces

PCA is applied on pre-processed face images for feature extraction. Eigen faces are computed from the input image which contains a small set of essential characteristics of the face image. Once the Eigen values of the face image are computed the projection is found in the new set of dimensions. A resulting image with extracted features is shown in Fig.8 (b).

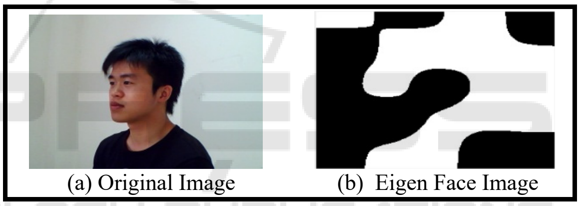

Figure 8: Representation of a Eigen Face of a Input Face Image

3.2.3 Iris

Effect of PCA on iris image is depicted in Fig.9.

Figure 9: Representation of an iris image to resulting feature image.

3.3 Feature Fusion

The wavelet transform is a mechanism by which data or operators or functions were cuts up into various frequency components and analyzes each component with a resolution matched to its scale. The aim of a pattern recognition system is to obtain the best possible classification performance. The better classification is obtained if the feature set is optimal. The three prime fusion strategies are:

- Information or Data Fusion:- More meaningful raw data is produced by data fusion, by combining obtained data from various sources.
- Feature Fusion:- The extracted feature set contains irrelevant and redundant features. If two features are of similar types then one of them must be redundant and we need only to keep any one of them. A feature is irrelevant if it does not strongly correlate the class information. The aim of feature fusion technique is to obtain a better feature set by fusing features, which may further given to classifier to obtain the final result.
- Decision Fusion:- A set of classifiers are used to provide unbiased and better result. Classifiers may be the same or different.

Wavelet Transformation (WT) is used for feature fusion. WT is an efficient method of image fusion which is capable of combining images which are from different sensors and sensing environments. The wavelet transform of the image is first computed. The computed wavelet transform of images contains different type of bands like high-high, high-low and low-high at various scales. To make this uniform the average is computed of all computed transform values. Max rule is applied to compute the larger value because the larger absolute transform coefficient corresponds to the sharp brightness changes to the image, which is the salient feature of the image (Li, 1995)(Andra, 2002)(Mangai, 2010)(Hubbard, 1998).

Effects of feature fusion using wavelet transform on fingerprints, faces, and iris images are shown in Fig.10, Fig.11, and Fig.12 respectively.

3.4 Training and Testing

Performance of Machine learning is derived from the fact that how well system is trained. A well trained system more sensitive to error detection. First we test the system for the data set and then test are performed to measure the performance of the system. How a system behaves for unseen data determines its performance. If the system behaves well to an unseen data and successfully predicts its class then it improves the performance otherwise it generates error. Deep leaning is applied here for the training and testing of the proposed model. More specifically Convolution Neural Network (CNN) is used. The reason behind the use of deep learning method is that neural networks are a powerful technology for classification of visual inputs. The most important practice is getting a training set as larger as possible (Simard, 2003).

Recognition is performed by using Convolution Neural Network (CNN) in the proposed work. CNN is a very powerful tool for character, speech and visuals which includes image as well as video recognition. A CNN is composed of many processing layers which gives it power to minutely observe the object and making it a powerful tool. It uses a hierarchy of layers to extract features where output of one layer became the input for the next layer in hierarchy. There are four key concepts behind convolution neural networks, which are: Use of multiple layers, Local Connections, shared weights and pooling.

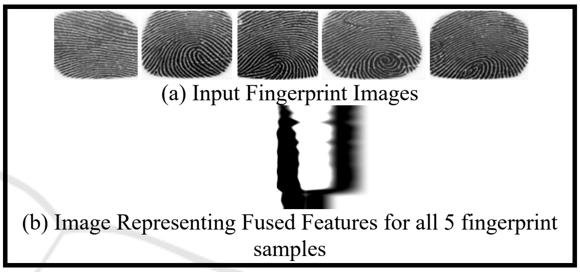

Figure 10: Fingerprint Feature Fusion

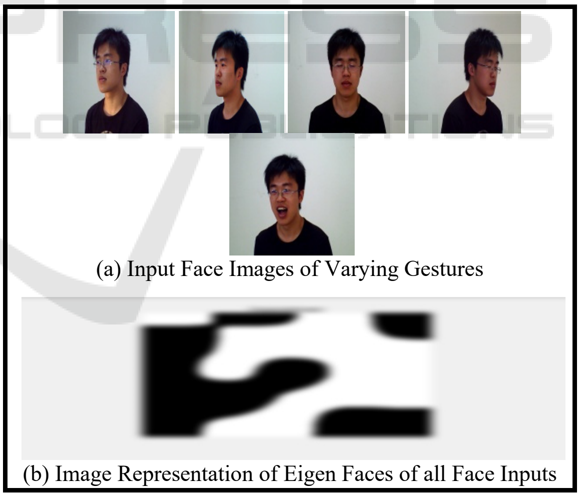

Figure 11: Representation of Fused Feature Eigen Image of Input Face Images.

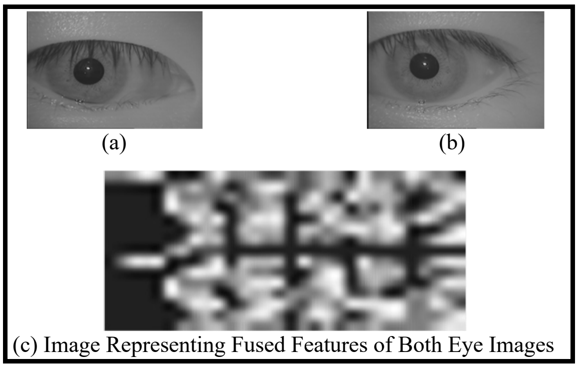

Figure 12: Representation of Fused Feature Image of Input Eye Images: (a) Input Image of Left Eye, (b) Input Image of Right Eye

Many natural signals are combination of hierarchies, and deep neural networks get the benefit of this composition. In these hierarchies, lower level features generates the higher level features. In images local combinations of edges form some specific patterns, parts are obtained by assembling these patterns, and parts form objects. When the elements vary in their position and appearance in previous layer, it allows to vary very little in the next layer with the help of pooling.

There is a concept of simple cells and complex cells in visual neuroscience. In CNN the convolution layer is inspired by simple cells and pooling layer is inspired by complex cells. Convolution and pooling layer compose the few early layers of CNN. Feature maps organize the units of convolution layer. Feature maps contain the patches. The pooling layer is used to merge features whose semantics are same.

The method used by CNN is very similar to animal's visual cortex. The image is processed in the form of independent small portions which is generally termed as visual fields. Each visual field is processed by separate neurons which are stacked in layers. Some of most used layers are: Convolution Layer, Pooling Layer, Locally Connect Layer and Fully Connected Layer (Le, 2015)(Krizhevsky, 2012)(Dũng, 2014).

4 RESULTS AND DISCUSSION

Experimental work is performed using SDUMLA-HMT database. This database contains biometrics samples of total 106 persons with 5 traits per person which are face, fingerprint, iris, finger veins, and gait. It includes 61 males and 45 females with the age between 17 and 31. Out of 5 biometric traits present in the database only 3 are of our interests which are Face, Fingerprint, and Iris. From the database, a separate cluster of 3 traits of all 106 persons is created which includes 5 random samples of faces with different gestures, 5 fingerprints, and 2 iris images left and right. Hence the database contains a total of 1272 images.

Out of 106 entries from database 100 persons are registered and their corresponding fused feature images are stored 3 per person, 1 fused image of all 5 face gestures, 1 fused image of all 5 fingerprints samples and 1 fused image of two iris samples. Out of 100 sets 80 are used for training and 20 are used for testing. When CNN is applied for train test its accuracy was 96.67%, while the error was 3.33% with elapsed time for .77(approx.) for testing where 1 epoch is used and for training it is .55 and .33 seconds where number of epoch used is 2.

A plot between number of epoch multiplied by number of batches versus CNN loss. Since number of epoch in testing is 1, hence graph is considered between number of batches and CNN loss. The vertical axis represents the CNN loss and horizontal axis representing the number of batches. The graph is shown in Fig.13.

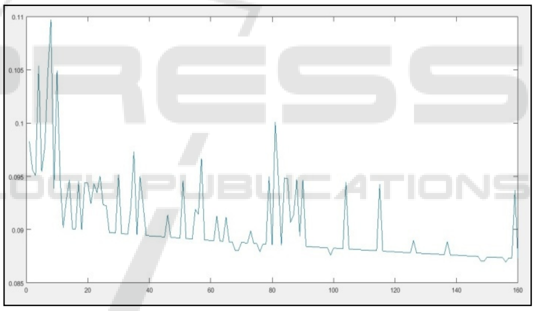

Figure 13: Plot CNN Loss (Vertical) Vs No. of Batches (Horizontal)

Table-I shows some result comparisons with existing latest Multimodal systems available. This table contains 5 columns as depicted. Here four key parameters are selected for result comparison, which are: Traits, Method, Accuracy and Elapsed time. Most multimodals use three traits, but few with 2 traits also exist. Use of only two traits may perform better in terms of time and recognition rates, but reliability may get affected in some cases. It is easily observed that accuracy of some existing modals is slightly better than accuracy achieved in this work. This is because of two reasons. The first reason is that, use of different datasets. It is observed in literature survey that recognition rate of a particular method varies large with the change of datasets. The second reason is the kind of methods being used. A method with high recognition rate may take large extent of time in comparison with deep learning method. Deep learning method is much faster than other methods and this can be easily observed by the Table-I. The only limitation of deep learning method is that it requires large data sets to perform better. And when we use a fused modal with deep learning then it may get a much reduced dataset in comparison with actual one. Here we have used a large data set but because of feature fusion the size of dataset is reduced up to 75% and deep learning is applied only 25% of the actual dataset. But the proposed work is able to perform better than existing modals, which are based on deep learning method. The elapsed time of deep learning approach is far better than other methods.

Table 1.

Title	Traits	Method	Accuracy	Elapsed Time(S)
Shams M., Tolba A, & Sarhan S (2016).	Face, Fingerprint, Iris	LBPV	99.50%	24 Sec.
Choi H. & Park H. (2015).	Face, Gesture	4-Fold Cross Validation	97.59%-99.36 %	--
Khoo Y. H., et.al. (2018, June	Iris, Fingerprint	IFO-Hashing	99.2%	--
Ammour B, Bouden T, & Amira-Biad S (2017	Face, Iris	Snake, DCT, Z-Score	87%, 94%, 98%	2.623Sec., 15.82Sec., --
This Work	Face, Fingerprint, Iris	PCA, WT, Deep Learning	96.67%	.77 Sec

5 CONCLUSIONS

This paper proposed a biometric identification system based on a multimodal by using feature fusion technique. Identifying a person using only a single trait is not optimal always due to several problems like physical loss of traits, medical reasons or any other reasons. Using a multimodal minimizes that risk in comparisons to uni-modals by providing extra set of information. Here, three most frequent traits of human such as Faces, Fingerprints and Iris have been used for biometric recognition. In this paper PCA and WT were used feature extraction and feature fusion respectively. This paper has been proposed a CNN based model with fused feature of three biometric traits to recognize the biometrics. The proposed approach has been achieved the accuracy up to 96.67%.

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