Deep learning approach for Touchless Palmprint Recognition based on Alexnet and Fuzzy Support Vector Machine

Original Scientific Paper

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Abstract *– Due to stable and discriminative features, palmprint-based biometrics has been gaining popularity in recent years. Most of the traditional palmprint recognition systems are designed with a group of hand-crafted features that ignores some additional features. For tackling the problem described above, a Convolution Neural Network (CNN) model inspired by Alex-net that learns the features from the ROI images and classifies using a fuzzy support vector machine is proposed. The output of the CNN is fed as input to the fuzzy Support vector machine. The CNN's receptive field aids in extracting the most discriminative features from the palmprint images, and Fuzzy SVM results in a robust classification. The experiments are conducted on popular contactless datasets such as IITD, POLYU2, Tongji, and CASIA databases. Results demonstrate our approach outperformers several state-of-art techniques for palmprint recognition. Using this approach, we obtain 99.98% testing accuracy for the Tongji dataset and 99.76 % for the POLYU-II datasets.*

Keywords*: Palmprint Recognition, Deep learning, Support Vector Machine, Fuzzy*

1. INTRODUCTION

Palmprint recognition has recently become a study of interest in image processing, artificial intelligence, and pattern recognition as a type of biometric technology. It is a popular biometric with several advantages, including stable line features, which can handle low-resolution imaging, and cheaper capturing devices with ease of use. Palmprint images have rich and discriminative features that allow for reliable person identification. Existing palmprint recognition methods may be categorized into strategies based on structuring, texture, subspace, and statistics. Structure-based techniques are utilized to obtain relevant line and point features [1][2]. However, the recognition accuracy in structure-based approaches is low. Further, the features demand higher storage space. In texture-based techniques, rich texture information from palmprints will be extracted [3][4][5]. These methods have better classification capabilities with higher recognition accuracy. In these methods, the coding of palmprint features is carried out. Therefore they could be influenced by image translation and rotation. In subspace-based techniques, images are transformed and mapped from their higher dimensional representation to lower-dimensional vector space [6][7].

These approaches have higher accuracy and recognition speed. Additionally, most of these features are created by a biometric specialist and are hand-crafted to accomplish better performance with a specific type of biometric dataset. Conventional image-based palmprint recognition systems have drawbacks such as pre-processing, parameter settings, and hand-crafted features that need to be carried out by biometric specialists. Several techniques and applications have recently included deep learning for biometric identification. A variety of patterns are being used to train the deep network. Once the deep learning model has learned the dataset's unique characteristics, it can be incorporated to identify similar patterns. Deep learning techniques have primarily been utilized to acquire features for palmprint recognition [8][9][10].

Additionally, deep learning can be highly effective for classification and clustering tasks. The system classifies the input examples according to their associated class labels during the classification task. In contrast, when performing a clustering task, the instances are clustered according to their similarity without reference to class labels. Numerous methodologies discussed below are built on deep learning techniques for recognizing palmprints. Within the deep learning framework, the input images are fed to the CNNs, determining the optimal way to merge the pixels to obtain maximum recognition accuracy. Wang et al. [11] used two-dimensional Gabor wavelets to decompose the palmprint images. In this work, PCNN (Pulse-Coupled Neural Network) is employed to simulate the perceptive function of creatural vision and break down every Gabor sub-band together into a sequence of binary images. Entropies are computed for the binary images and are considered features. For classification, the SVM-based classifier is used.

To create a better genuine score distribution of touchless palmprint datasets, Svoboda et al. [12] suggested a CNN using the AlexNet model, which is trained by optimizing a loss function linked to the d-prime index. Minaee et al. [13] devised a palmprint recognition system based on a deep scattering CNN with two layers. Then, Principal Component Analysis(PCA) is employed for dimensionality reduction of the data. A multiclass Support Vector Machine and nearest-neighbor classifiers are used to perform the classification task. Meraoumia et al. [14] proposed a model for deep learning called PCANet for feature extraction of the palmprint. They experimented with Random Forest Transform(RFT), KNN, Radial Basis Function(RBF), and SVM classifiers for the multispectral datasets. Cheng et al. [15] proposed a technique called DCFSH that extracts palmprint convolutional features using CNN-F architecture, then learned binary coding from distilled features. A multispectral palmprint database is used to analyze DCFSH. The Hamming distance is used for matching. In [16], the palmprint images are preprocessed using a fuzzy enhancement algorithm and then trained using Alexnet, which results in higher accuracy than some conventional techniques. Zhong et al. [17] suggested a novel approach for end-to-end palmprint identification through a Siamese network. Two parameter-sharing VGG-16 networks are employed in the network to retrieve convolutional features from two input palmprint images. The top network obtained similarity in two input palmprints directly from convolutional features. Khaled Bensid et al. [18] proposed a discrete cosine transform network (DCTNet) deep feature extraction algorithm for palmprint recognition for multispectral datasets. Genovese et al. [19] introduced PalmNet. This convolutional network employs Gabor responses and PCA filters in an unsupervised approach on several touchless palmprint databases and performs classification using a 1-NN classifier based on Euclidean distance. Gong et al. [20] used Alexnet with the PRelu activation function for palmprint recognition. In [21], a pre-trained MobileNet V2 neural network is applied to learn the palmprint features, and linear SVM is used for the classification to obtain higher accuracy. Zhao et al. [22] developed a Joint Constrained Least-Square Regression model using the CNN model to address the under-sampling classification task by extracting various deep local convolutional features from multiple patches from the same palmprint image. Veigas et al. [23] proposed a genetic-based 2D Gabor filter with CNN for palmprint recognition. The filters are tuned using a genetic algorithm, and Gabor features are extracted.

Liu et al. [24] proposed SMHNet that extracts features of the palmprint at structure and pixel levels. Recently, many biometric initiatives are increasingly being explored using deep learning techniques because of the capability to extract features from noisy data and adjust to biometric data samples captured with various devices and achieve good recognition in less-constrained environments. Numerous CNNs, such as AlexNet, VGG-Net, Inception-V3, and ResNet, perform better at image recognition and classification [25].

Although CNN-based techniques efficiently capture perceptual and biometric information extracted from the input images, applying this approach to verify palmprints poses some challenges. Firstly, the sample size is a constraint in existing palmprint databases, as most CNN approaches require a substantial quantity of input data during the training phase. Secondly, the performance of CNNs is highly dependent on the underlying architecture. Due to the above-stated limitations, utilizing a CNN architecture in small datasets may result in overfitting. It is observed that data augmentation strategies are only marginally effective in reducing overfitting due to the low intra-class variability of palmprint images.

Although the pre-trained CNN model may be faster, there is another approach called Transfer learning [26]. Transfer learning is typically used to solve problems where the datasets include insufficient data to train a full-scale model from the start. Transfer learning is a process that adopts previously trained CNN, removing fully connected layers and also training the remaining layers from the required dataset. A CNN may obtain discriminative features of the image by freezing the weights of CNN layers and fully connected layers for classifying palmprint images. These addresses the challenges associated with CNN approaches that include substantial computational cost during the learning phase and overfitting induced by tiny palmprint databases.

As per the above literature survey, Alexnet has been widely used and yielded better results than other deep networks. Besides, the Alexnet has a simple architecture and can be trained with a few epochs. Therefore, Alexnet has been chosen for this work.

SVM is a discriminant method that analytically solves the problem of convex optimization and gives some optimal hyperplane parameters, unlike perceptron which are mostly used in machine learning for classification. In the case of perceptrons, the solutions depend on the criteria of initialization and termination. To address the highly nonlinear problem, kernels like RBF(Radial Basis Function) are used. Although kernel SVM solves the nonlinear problem, it cannot optimally give a solution for the hard boundary conditions [27]. Hence, fuzzy SVM have been chosen for classifying the palmprint and solving hard boundary condition.

The main contribution of this work is as follows:

- Proposed a fuzzy SVM classification approach for the palmprint recognition that provides better classification accuracy.
- Proposed a framework using transfer learning and fine-tuning the Alexnet model for feature extraction.
- Extensive experimentation is performed on four openly accessible palmprint datasets: PolyU-II, CASIA, Tongji, and IITD Contactless databases.
- Systematic analysis is performed by comparing the proposed approach with eight different state-of-the-art schemes such as CR-CompCode, LLDP, HOL, LDP, LBP, AlexNet, VGG-16, and VGG-19

The remainder of the paper is discussed as follows: Section-2 demonstrates the proposed methodology. Section-3 presents the implementation and results. Lastly, the conclusion of the work.

2. METHODOLOGY

2.1 IMAGE PREPROCESSING

After capturing the image, pre-processing is the most crucial step in developing any biometric system. First, the Region of Interest is extracted using the techniques mentioned in [23]. In the pre-processing step, the noise or any other artifacts are removed. The image is enhanced using a fuzzy enhancement algorithm [28], using the membership function with a fuzzy enhancement operator built up of piecewise continuous function. The fuzzy membership function is given by Eqn. (1).

$$P_{ij} = F\left(X_{ij}\right) = \left\{ \begin{array}{c} s_1\, tg^2\left(\frac{\pi X_{ij}}{4(L-1)}\right) \ldots 0 \leq X_{ij} \leq X_T \\ 1 - s_2\left(1 - tg\,\frac{\pi X_{ij}}{4(L-1)}\right)^2 \ldots X_T < X_{ij} \leq L-1 \end{array} \right\} \quad (1)$$

The general idea behind the fuzzy enhancement algorithm is to perform weakening and strengthening the operations in low grey scale and high grey scale regions, respectively. Thereby the pixel's grey levels will decrease in the low scale region and increase in the high grey scale region. The enhanced ROI is given as an input to train the convolutional neural network.

2.2 CONVOLUTION NEURAL NETWORK(CNN)

CNN is a well-studied and widely applied branch of deep learning. It is a multi-layered network model, which is improved from back propagation neural network. The network uses forward propagation to compute output values and back propagation to fine-tune weights and biases. In contrast to the traditional recognition algorithm, the CNN repetitively performs convolution and pooling on the original input to produce progressively complex feature vectors and delivers the output directly via the fully connected neural network. It consists of five layers: the input layer, the convolution layer, the pooling layer, the full connection layer, and finally, the output layer. Convolutional neural networks are made use in extracting features from the image.

2.3 SUPPORT VECTOR MACHINE(SVM)

SVM is one of the successful computational mathematical models for solving classification problems. The SVM algorithm is capable of classifying both linear and nonlinear data. Support vector machines are algorithms that create a hyperplane or a series of hyperplanes by transforming the training data into multidimensional or infinite-dimensional space. These hyperplanes are referred to as decision planes or decision boundaries.

For the binary linear classification problem, the hyperplane is defined using Vapnik's theory [29]. Given input training dataset of the form (x_i,y_i), where x_i belongs to the class for which $y_i \in \{-1,1\}$. It is required to obtain a hyperplane that separates the classes such that

$$w.\varphi(x_i) + b = 0 \quad (2)$$

where z is a vector and b is a scalar that separates the points in the class x_i. The two sides of the hyper plane meet the inequality function criteria which is given by

$$w.\varphi(x_i) + b \geq 1 \;, where\ if\ y_i = 1 \quad (3)$$

$$w.\varphi(x_i) + b < -1 \;, where\ if\ y_i = -1 \quad (4)$$

The smallest perpendicular distance from the hyperplane to the data point is called the margin. The decision plane with the largest margin is known as the maximum marginal hyperplane. The maximum boundary separating hyperplane is chosen by SVM. SVM's maximum marginal hyperplane selection improves classification accuracy and reduces the likelihood of misclassification.

In Non-linear SVM, separation is obtained by mapping the n-dimensional input feature vector x into to the k-dimensional feature vector using the nonlinear vector function φ(x). We then construct the decision function f(x) that distinguishes data from between two different classes in the feature vector.

$$f(x) = w^T\, \varphi(x) + b \quad (5)$$

where w and b are the k-dimensional feature vector and biased term, respectively.

The L1-SVM is then expressed in its primitive form given as follows:

$$P(w,b,\varepsilon)=\frac{1}{2}w^Tw+R\sum_{i=1}^{m}\varepsilon_i \tag{6}$$

which is constrained to $y_i f(x_i)\geq 1-\varepsilon_i,\ \forall_i=\{1,2,\dots m\}$ where R is the boundary parameter which regulates the trade-off involving training error and generalization ability, xi is a set of M n-dimensional training inputs that belongs to either Class1 or Class2, and the corresponding labels are y_i=1 and y_i=-1 for both the classes, respectively, given that the slack variable $\varepsilon_i\geq 0\ \ \forall_i=\{1,2,\dots m\}$.

Multi Class SVM

Multiclass SVM attempts to assign labels to a set of multiple items which depend on a set of either linear or nonlinear basic SVMs. In the literature [30][32], a common way to accomplish this is to divide the single multiclass problem into numerous binary class problems. There are two approaches:

One-vs-rest (OVR) approach is the simplest way to extend SVMs for multiclass problems. It involves breaking down the multiclass dataset into several binary classification problems. Here, n linear SVMs are trained separately, while data from other classes become negative cases. A binary classifier is trained on each binary classification problem, and predictions are made using the most confident model. Initially, the binary classifier is trained for a given class using the training samples. These samples are separated from the rest of the class samples. In the classification, x is classified into a multi-label class which is given as follows:

$$L_c=\{k\mid f(x)>0\ \ for\ k=1,\dots m\} \tag{7}$$

where m represents the number of classes. This approach is called binary relevance method or OVR. This is an augmentation of single-label one-vs-rest classification.

One-vs-one (OVO) approach: It creates M*(M-1)/2 binary classifiers by forming the combination of binary pair-wise possibilities of the M classes.

In[31], it is observed that OVR is superior as compared to OVO approach.

Fuzzy support vector machines

Given a M class problem with class labels 1 to M, we specify distinct class labels from M+1 to N to the target training dataset, in which number of newly created classes are N-M. These classes are called multi-label classes. Here, class 1 to class m is single-labeled class The remaining k number of multi-label classes contains single-labeled classes k_1 to k_e, where $L_{k_e}=\{k_1,k_2\dots k_e\}\in L_m=\{1,2\dots,m\}$.

Given an optimal boundary fi(x) = 0 which separates the training samples of class i from the rest of the other class samples, then the convex region is given by

$$R_k=\left\{x\middle|\ \begin{Bmatrix} f_i(x)>0, & i\in L_{k_e} \\ f_i(x)<0, & i\in L_m-L_{k_e}\end{Bmatrix}\right\} for\ k \\ =\{1,2\dots m\} \tag{8}$$

Where R_k represents the region for class k which contains all the training samples for class k, wherein if class k denotes a single-labeled class, then 1≤ k ≤ n, k_1=k_e=k.

Suppose we want to classify training data x into one of m distinct classes. It is accomplished by defining a membership decision function for x within the region Rk where k= {1...m}.

By introducing a fuzzy membership function [31] $fz_{ij}(x_i)$ on the direction perpendicular to decision function $f_{ij}(x)$=0 as

$$fz_{ij}(x)=\begin{Bmatrix} 1 & for\ f_{ij}(x)\ \geq 1 \\ f_{ij}(x) & otherwise\end{Bmatrix} \tag{9}$$

Given $fz_{ij}(x)$ (i≠j, j=1, 2... m) the membership function of x belonging to a class i is given as

$$fz_i(x)=min_{j=1,2..m}f_{ij}(x) \tag{10}$$

Which is also expressed as

$$fz_i(x)=min\left(1,min_{i\neq j,j=1,\dots m}f_{ij}(x)\right) \tag{11}$$

Finally, a given unknown sample x is classified using

$$arg\ max_{i=1,2,\dots m}fz_i(x) \tag{12}$$

Feature Extraction and Classification

Figure 1 shows the block diagram of the proposed work. The input required for the model is 224x224x3 pixel size. Hence, ROI is resized to fit to the network requirements. The model used here is Alexnet, which is consists of five convolutional layers and three fully connected ones. The convolutional layers are given as follows:

96 kernels of size 55 x 55 x 3 in the first layer, 256 kernels of size 5 x 5 x 64 in the second layer, and 256 kernels of size 3x3x256 in the following three layers. They are followed by two fully connected (FC)layers with 4096 neurons. In the final layer, a fuzzy SVM classifier is used.

3. IMPLEMENTATION AND RESULT

This section shows the implementation and results obtained for the various standard databases. The experiments are implemented using Intel(R) Xeon(R) 2.30 GHz with NVIDIA Tesla K80 GPU. The final result is evaluated using accuracy, EER, and Receiver Operating Characteristics Curves.

3.1 DATABASES USED

The presented methodology is evaluated using four openly available databases: CASIA[33], PolyU-II[34], IITD[35], and Tongji[36]. The CASIA Palmprint Database contains 5502 palmprint images from 312 different persons. The palmprint database at the IITD has 2601 images from 460 palms associated to 230 individuals. PolyU-II database has 7752 grayscale palmprint images in the collection containing 386 palmprint images. In the Tongji dataset, there are 6000 images belonging to 600 people.

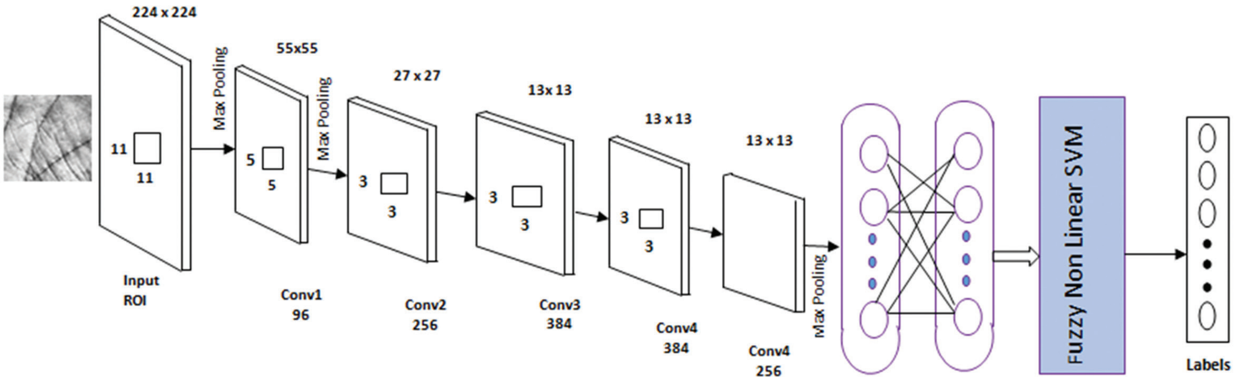

Fig. 1. Proposed Block diagram

3.2 EXPERIMENTAL RESULTS

The proposed model is assessed based in terms of accuracy using the equation-13. The accuracy of the classifier is given by ratio of correct image classification to the total number of images.

$$accuracy = \frac{(T\_P + T\_N)}{S} \tag{13}$$

Where T_P, T_N, S are true positive, true negative, and total number of sample images to be classified respectively. To perform the experimentation, we split the dataset into two parts: training dataset and testing dataset in the ratio of 80% and 20 % respectively.

Table 1. Comparison of Validation accuracy

Sl no	Method[Ref]	Classification accuracy (%)			
		IITD	POLYU-II	Tongji	CASIA
1	LBP[37]	92.81	98.2	98.9	97.3
2	LDP[38]	85.17	95.18	99.28	98.91
3	HOL[39]	95.90	98.3	99.21	98.96
4	CR-Compcode[40]	94.44	98.88	99.11	96.33
5	PCANet[14]	98.63	99.45	99.78	98.37
6	VGG-16[41]	92.56	94.28	97.14	92.14
7	VGG-19[41]	92.25	94.22	96.04	92.16
8	AlexNet[20]	96.1	98.88	99.32	96.73
	proposed	98.78	99.76	99.98	98.93

Table 1shows the accuracy of the proposed method with the already existing methods in palmprint identification experiments, all of which were evaluated on the PolyU-II, IITD, CASIA, and Tongji databases. To configure the methods mentioned above, we use the parameters made available by the researchers. Our technique is compared to the newly published techniques known in the literature. To make comparisons against methods built on local-based texture descriptors, we have used the CR-CompCode, LLDP, HOL, LDP, and LBP approaches. We compared PCANet with the pre-trained AlexNet, VGG-16, and VGG-19 CNNs as deep learning approaches. The experimental results show that the classification accuracy of the proposed method for the IITD database has an improvement of 2.68 %,6.53%, and 6.22% compared to the pre-trained Alexnet, VGG-16, and VGG-19, respectively, as shown in Table 1. The accuracy of PCAnet is on par with the proposed approach. But the amount of training time taken in PCAnet is more than the proposed approach. The proposed method has an improvement of 0.31%,5.48%,5.54%, and 0.88% when compared with the planet, VGG-16, VGG-19, and Alexnet, respectively, for the PolyU-II dataset. In the case of the Tongji database, the proposed approach has an improvement of 0.2%,2.84%,3.94%, and 0.66% for PCAnet, VGG-16, VGG-19, and Alexnet, respectively.

Traditional approaches based on local texture descriptors [37-40] reveal performance variations on different databases. However, the proposed CNNs have consistent accuracy across all databases experimented with. The recognition accuracy is highest in the Tongji dataset compared with the other datasets considered for this experiment. The data analysis shows the proposed method's classification accuracy, which is consistent across all the datasets with accuracy >98%. The advantage of fuzzy SVM is that it classifies the palmprint and solves hard boundary conditions.

The results of palmprint recognition are studied in terms of Equal Error Rate (EER), where the False Acceptance Rate (FAR) and False Rejection Rate (FRR) are the same. Table-2 shows the comparison of EER% for the different methods for the palmprint recognition for the considered databases. It has been observed that the proposed approach produces the least EER in the Tongi database with the EER % of 0.16 and performs consistently better than other approaches for other datasets.

Table 2. Comparison of EER%

Sl no	Method[Ref]	Classification accuracy (%)			
		IITD	POLYU-II	Tongji	CASIA
1	LBP[37]	10.79	3.62	1.70	4.37
2	LDP[38]	18.87	4.82	2.44	4.84
3	HOL[39]	6.7	0.31	0.41	4.62
4	CR-Compcode[40]	4.65	0.89	0.47	3.67
5	PCANet[14]	1.37	0.43	0.20	1.63
6	VGG-16[41]	7.44	5.72	2.86	7.86
7	VGG-19[41]	7.75	5.8	3.96	7.84
8	AlexNet[20]	3.90	2.01	0.68	3.22
	proposed	1.22	0.84	0.16	2.42

Figure 2 depicts the training accuracy and validation accuracy versus Epochs. The graph shows that with almost 10 Epochs, the accuracy is reached nearly above 95%. The learning rate is kept at 0.001.

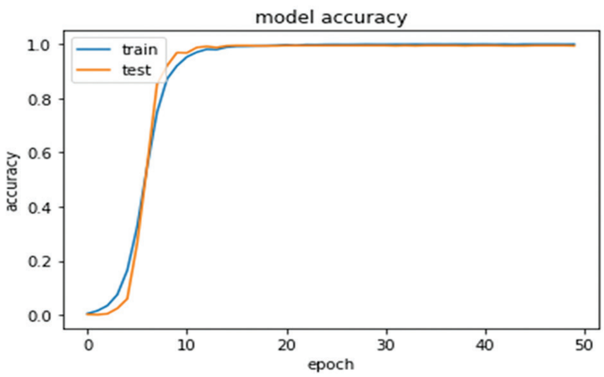

Fig. 2. Accuracy vs Epochs

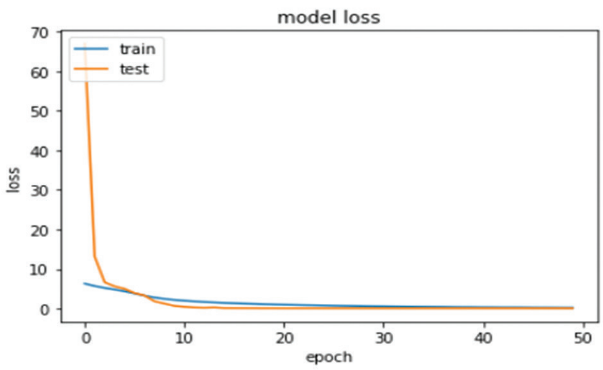

Fig. 3. Loss vs Epochs

Receiver Operating Characteristic:

The receiver operating characteristic (ROC) curve is a graphical illustration of the trade-off between genuine acceptance rate (GAR) and false acceptance rate (FAR) represented in the y and x coordinates respectively. The GAR and FAR equations are as follows:

$$GAR = \frac{T\_P}{T\_P + F\_N'} \quad (14)$$

$$FAR = \frac{F\_P}{T\_P + F\_N'} \quad (15)$$

Measuring the area under the ROC curves is a reliable approach to comparing the performance of the different classifiers. Figure 4-7 shows the ROC curves of various techniques and multiple datasets. The proposed work has achieved high GAR and low EER with the different datasets and various benchmark methods. It is observed from the graph that the ROC for the approximate coefficients is close to the optimal ROC curve. AUC lies between the values 0.95 to 1.0 which shows that the classifier is very efficient.

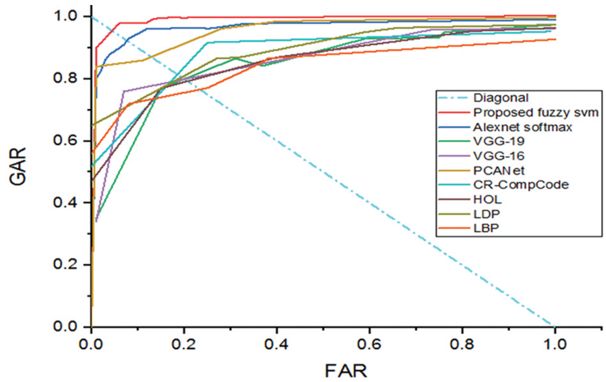

Fig. 4. ROC curve analysis for the proposed method using Tongji DataSet

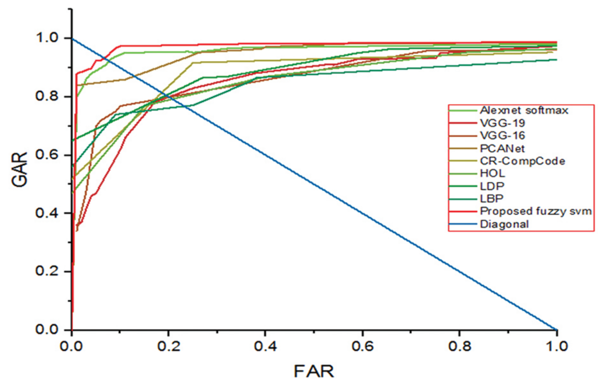

Fig. 5. ROC curve analysis for the proposed model with other methods for IITD dataset

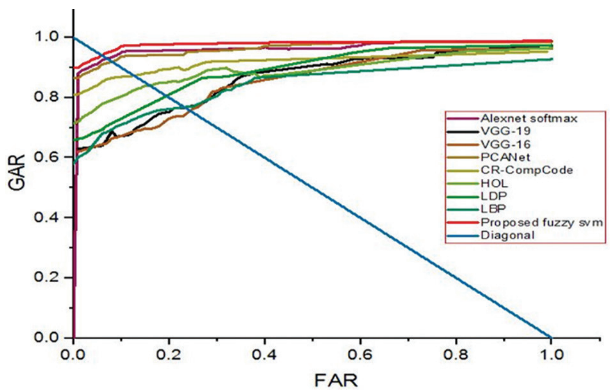

Fig. 6. ROC curve analysis for the proposed model with other methods for POLYU2 dataset

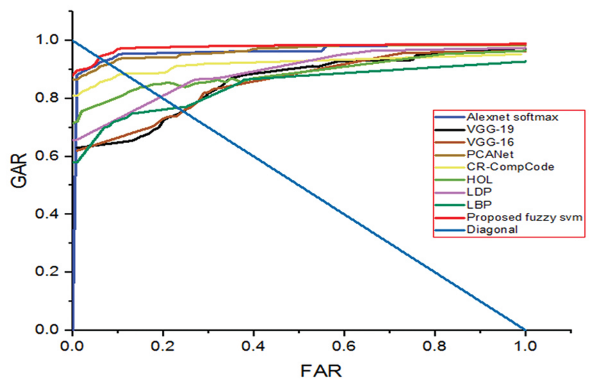

Fig. 7. ROC curve analysis for the proposed model with other methods for CASIA dataset

4. CONCLUSION AND FUTURE WORK

The presented paper proposes Convolution Neural Network (CNN) inspired by Alex-net to learn the features, and a fuzzy support vector machine is used for classification. The output of the CNN is fed as input for the support vector machine. The CNN's receptive field aids in extracting the most discriminative features from the palmprint images, and Fuzzy SVM results in a robust classification. The experiments are conducted on popular contactless datasets such as IITD, POLYU2, Tongji, and CASIA databases. Results demonstrate our approach outperformers several state-of-art techniques for palmprint recognition. Results show that the proposed method is efficient with good accuracy and very low EER values compared to the several state-of-art methods. Analysis of the ROC curves demonstrates that the proposed techniques' have higher accuracy on all databases evaluated based on Genuine Acceptance Rate and Acceptance Rate values. The fuzzy SVM is not feasible for large overlapping class labels, and one can overcome this disadvantage by using evolutionary or quantum computing techniques.

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