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An intelligent system for automatic fingerprint identification using feature fusion by Gabor filter and deep learning

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ABSTRACT

This paper introduces an intelligent computational approach to automatically authenticate fingerprint for personal identification and verification. The feature vector is formed using combined features obtained from Gabor filtering technique and deep learning technique such as Convolutional Neural Network (CNN). Principle Component Analysis (PCA) has been performed on the feature vectors to reduce the overfitting problems in order to make the classification results more accurate and reliable. A multiclass classifier has been trained using the extracted features. Experiments performed using standard public databases demonstrated that the proposed approach showed better performance with regard to accuracy (99.87%) compared to the more recent classification techniques such as Support Vector Machine (97.86%) or Random Forest (95.47%). However, the proposed method also showed higher accuracy compared to other validation approaches such as K-fold (98.89%) and generalization (97.75%). Furthermore, these results were supported by confusion matrix results where only 10 failures were found when tested with 5000 images.

1. Introduction

Biometric recognition is one of the promising authenticating systems worldwide. It uses a verification process that involves biological feature like face, fingerprint, hand veins, iris, retina etc. [1]. However, fingerprint identification and verification are widely used as biometric technique due to its simplicity, distinctiveness, and long lasting properties. Fingerprint plays a great role in ensuring public security and criminal investigation including forensic investigation, law execution, tax access and public security. Minutiae-based technique has become the popular fingerprint matching algorithms such as phase and skeleton matching or image correlation [2]. Biometric identification systems are still slow and often they produce incorrect results. Sometimes noise present in the image during scanning biometric data causes distortion in the recognition results [3].

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A fingerprint is a distinct region on the fingertip based on ridges and valleys. The region is identified as different classes in the literature. The fingerprint classification based on individualities and neural network investigation was proposed in [4] using the NIST databases that was commonly utilized by a number of studies. The key challenge of their classification was acquiring the accurate number and singularity situation such as core and delta points. Transitional solution on fingerprint classification was developed by adopting neural network technique at the decision stage. The neural network was employed to perform matching technique for developing the way of recognizing and categorizing fingerprint by back propagation technique. The fingerprint classification, indexing, and reprocession theme were studied broadly in the past few decades. Most of the investigators faced one key challenge of publicly accessible fingerprint database, only a few sections of image for each individual are available for training and testing, which is inappropriate for sophisticated statistical classification. Leung and Leung [5] attempted to tackle this issue by first artificially expanding the training set using their spatial modeling technique and managed to obtain a better accuracy with Bayes classifier. Wan et al. [6] proposed XFinger-net method for identifying partially defective fingerprint image (PDFI) based on the fingerprint features. They have employed deep learning to segment defective and high noise fingerprints where 640 and 160 data were considered for the training and testing respectively. XFinger-Net method showed better performance although deviation in segmenting defective fingerprint could not be fully avoided. A study conducted by AlShehri et al. [7] found that fingerprint matching was more challenging on the images obtained by multiple sensors. Their analysis showed that minutiae were robust fingerprint features and VeriFinger provided best matching. Wu et al. [8] have proposed Convolutional Neural Network (CNN) model to identify patterns of real fingerprint. The authors have achieved a best accuracy of 94.87%, whereas an accuracy of 92.9% was also obtained for a four-category fingerprint database by the CNN model. Based on the results, it can be said that the proposed model can recognize the pattern features through automatic learning and feature extraction.

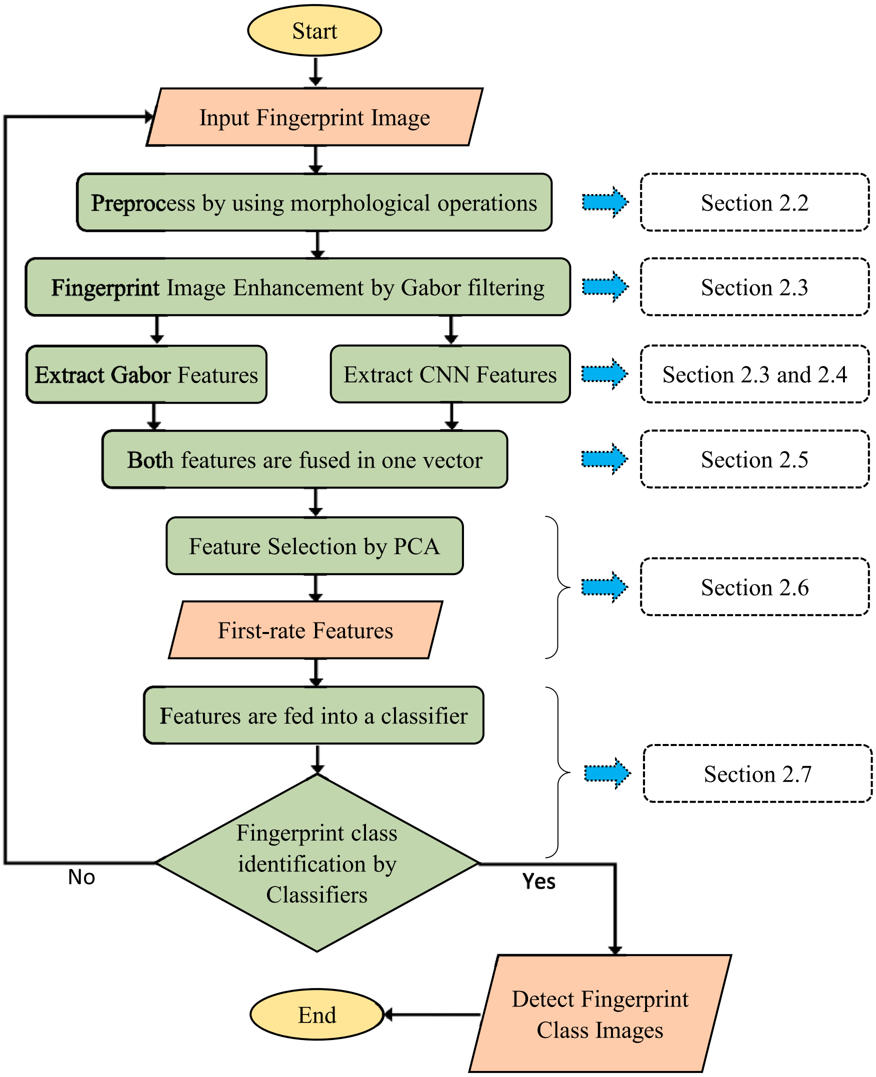

Fig. 1. Framework of the proposed methodology for fingerprint detection.

Takahashi et al. [9] presented a technique for collecting fingerprint features from texture, minutiae, and frequency spectrum using CNN and added a frequency spectrum as a new feature. A minutiae attention module was employed to identify the position of the minutiae to extract texture features and better performance was obtained by the proposed method than the traditional fingerprint recognition software

A method was proposed to retrieve missing feature elements from the information fixed in an image region of poor quality. Probabilistic Neural Network (PNN) was employed for conducting the classification task. In [10] an Adaptive Genetic Neural network (AGNN) was used for the classification of fingerprint images by performing experiments in three phases. First of all, the denoising procedure was performed using Wave atom transform in order to augment the fingerprint image followed by the application of some morphological operations, and finally they completed the procedure by ordering of the images. Peralta et al. [11] presented a convolutional neural network-based approach to classify fingerprint images belong to some given classes. They have arranged the fingerprints into disjoint classes as groups and performed the matching operations by comparing to the predicted classes. The authors suggested that this approach could reduce penetration rate of search and predict fingerprint class even for a low-quality image.

The convolutional neural network can play a great role to develop an intelligent system for fingerprint identification and verification. Traditional fingerprint matching algorithms may lead to a lack of extracted features information [12]. The matching features are not completely studied or categorized [13]. To overcome these issues, the deep neural networks have attracted attention of the researchers for their capability of complex pattern recognition..

The aim of this study is to create an intelligent system for classifying fingerprint image according to five unique classes by employing the fusion of deep learning and Gabor Filter instead of minutiae matching approach. Principal Component Analysis (PCA), a classical dimension-reduction and feature extraction algorithm, has been applied for further improving the classification performance [14]. The key contributions of this work are listed as:

a) Designing a trainable deep neural network using the fusion of Convolutional Neural Network (CNN) and Gabor features to classify the fingerprint image. The fusion approach increases the accuracy through extracting and fusing features from two feature extractors individually. The fusion technique provide a large number of easily identifiable features that can lead the system to classify the images more accurately.
b) Reducing the dimensionality of statistical features by using a PCA to improve the identification performance.
c) Comparing the accuracy of the proposed method with the existing recent methods.

The fusion of deep learning and Gabor filtering bring novelty in this work in obtaining unique and improved features compared to the features extracted by individual techniques. Therefore, images can be identified more efficiently and accurately. The remaining part of the paper has been arranged as follows. Section 2 presents investigation methods with relevant theoretical background. Experimental details are described in Section 3. The results of the present investigation on fingerprint identification are provided and critically discussed in Section 4. Finally, key conclusions are presented in Section 5.

2. Methodology and theory

2.1. Adopted methodology

The methodology for the system development is outlined sequentially in Fig. 1. From the captured fingerprint image, the proposed system extracts statistical features using Gabor Filters and CNN. Fusion of the features extracted by both the techniques as vector are fed into the classifiers followed by a PCA. The PCA is mainly used here to extract the statistical features of the identical central areas from the feature vectors. Then the image is catagorised into a specific class and identify the fingerprint according to this category.

The proposed system considered fingerprint images as an input and performed classification as an output. The experiment was performed on the standard fingerprint dataset with five fingerprint classes, such as, Arch, Tented Arch, Left-loop, Whorl and Right-loop. This paper used standard NIST datasets [15]. Three databases were used from the Fingerprint Verification Competition (FVC) 2000, 2002 and 2004 [16-18]. Database 1 contains 788 learning images and 100 test images. The image resolution was 300 dpi with a size of 256 $\times$ 256 pixels [16]. The images from Database 2 were divided to create a training dataset of 400 images and a testing dataset of 100 images [17]. Database 3 [18] containing 4000 fingerprint images (image size is 227 $\times$ 227) was employed for obtaining classification accuracy through most of the algorithms. From the three databases, only visually good images were selected for this investigation.

The computational process was carried out in MATLAB 2017b for image enhancement and segmentation by using morphological operation. Morphological operation was used to estimate orientation field of the broken ridges. This would help the Gabor filter to extract a good statistical information of Gabor features. Gabor filter was used for textural representation and segmentation [15]. The Gabor features and CNN features were used to form the fusion for fingerprint classification and detection. Gabor feature contains one vector (size of 1 $\times$ 72) and CNN contains another vector (size of 1 $\times$ 4096). When the two vectors with the same format is concatenated, the fused vector was contained in one row (size of 1 $\times$ 4168). To improve the accuracy and make the classification results more reliable, the PCA, a dimensionality reduction technique, was applied on the feature vector. Quality of the fingerprint image determines the performance of the proposed system. Therefore, an image enhancement procedure could be carried out to improve the image quality and contrast in order to reduce the processing time (i.e., comparison as well as response) of the classification method for identifying the fingerprint. In the case of an unauthentic fingerprint, the output would be detected as a fake one. The algorithm of the fusion approach is shown in Algorithm 1.

2.2. Mathematical morphology

Before adopting a fingerprint image into the proposed automatic system, it was preprocessed using a window of size 227×227 pixels. Then the morphological operations were performed to augment the ridges of the fingerprint images. The ridge width should be decreased so that the ridge end and bifurcates in the fingerprint could be detected easily. If any white portion was encircled by black color, this portion was also filled with black color. In some cases, the unwanted portion was removed from the broken ridge of fingerprint image where the ridge size was less than a specified length. This procedure was performed using erosion-dilation and area opening techniques of morphological operation.

Dilation: It was mainly used to grow an object in size by extracting the outer boundaries of the given fingerprint image. Dilation continuously filled the missing pixel of a broken ridge as it added pixels at the boundary of the objects. Having applied this operation, the object enlarged its regions, shrank the single hole and reduced the gap between two regions. Symbolically, a dilation can be denoted by I⊕S where I is the input image and S is the structuring element. The dilation of image I at position (x, y), denoted by Eq. (1), is the maximum value of the window outlined by S when the origin of S is at (x, y).

$$[\mathrm{I} \oplus \mathrm{S}](x, y) = \max_{(a,b)\ \epsilon\ S} \{\mathrm{I}(x-a,\ y-b)\} \tag{1}$$

The structuring element S is reflected about its origin by using (-a, -b) in the argument of the function.

Erosion: This was used as the complement operation of dilation to smooth the fingerprint image after dilation. It caused to loss of size by extracting inner boundaries of a fingerprint edge. Therefore, it can be used to remove the noisy connections between the two objects. The effect was sharpening the fingerprint image since the unwanted pixels were extruded. It can be denoted as I∅S, here I is the dilated image and defined by Eq. (2). The origin of S visits every pixel in I and replaces the pixel value with the minimum value of I covered by S.

$$[\mathrm{I} \varnothing \mathrm{S}](x, y) = \min_{(a,b)\ \epsilon\ S} \{\mathrm{I}(x+a,\ y+b)\} \tag{2}$$

The value x and y are incremented using (a, b) such that the value is minimum among the pixels of I coincided by S.

Area Opening: In the opening operation, the image was first eroded and then dilation was carried out to smoothen the contour of fingerprint image by clearing the narrow bridge and eliminating the minor extension present in the object.

Fig. 2 shows the morphological operations on a fingerprint image. Fig. 2(b) shows the expansion of the image pixels by using dilation technique. Fig. 2(c) shrinks the image pixels by using erosion techniques. Morphological opening techniques are used to extract large image features as shown in Fig. 2(d).

2.3. Gabor filter

Gabor filter was used in the proposed system to improve the ridges and relax the valleys by implementing short term Fourier transformation with Gaussian window in a spatial domain [3, 19]. It assisted in obtaining the deviations in the textures and characteristics in the fingerprint image for different orientations and scales. These statistical attributes generated the image features, which were greatly accentuated using the orientation and frequency information in the fingerprint image by tuning the Gabor filter [3]. An example of extracting textural information from the fingerprint image by applying the Gabor filter is presented in Fig. 3.

A set of Gabor filter has been used on image I(x, y) in different frequencies with different orientation using the Gabor function g(x, y) as defined by Eq. (3).

$$g(x,\ y) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos(2\pi\frac{x'}{l} + \varphi \tag{3}$$

Algorithm 1
Applied fusion based algorithm for extracting features.

Input: Fingerprint image and preprocessed.
Extraction: Extract Feature Matrix (f).
CNN Feature Vector (Fc).
Step 1: $\boldsymbol{Loadinputimagesanditslabels}$.
Step 2: $\boldsymbol{Spliteachcategoriesintothesimilarnumberofimages}$.
Step 3: $\boldsymbol{Loadpre - trainedCNN}$
Step 4: $\boldsymbol{Pre - processimagesforCNNAlexnetmodels}$
Step 5: $\boldsymbol{Splitthesetsoftheimagesintotrainingandtestingdata}$
Step 6: $\boldsymbol{Fc = Extractfeaturesfromthedeeperlayesofalexnetmodel}$
Gabor Filter (GF)
Step 1:$\boldsymbol{Dividequeryimageinto}16\boldsymbol{x}16\boldsymbol{sub - blocks}$
Step 2: Compute features for 4 different scales at 8 different angles to give 8 different angles for each scale.
Step 3: $\boldsymbol{Calculatemeanandstandarddeviationtoobtaingaborfeaturesvector}$
Step 4: $\boldsymbol{f_{gc} = gaborfeaturesvector}$
Fusion of features in Vector (V).
$\boldsymbol{V(fusionfeaturevector) = F_c + f_{gc}}$
Output: Extract fusion feature vector (V).

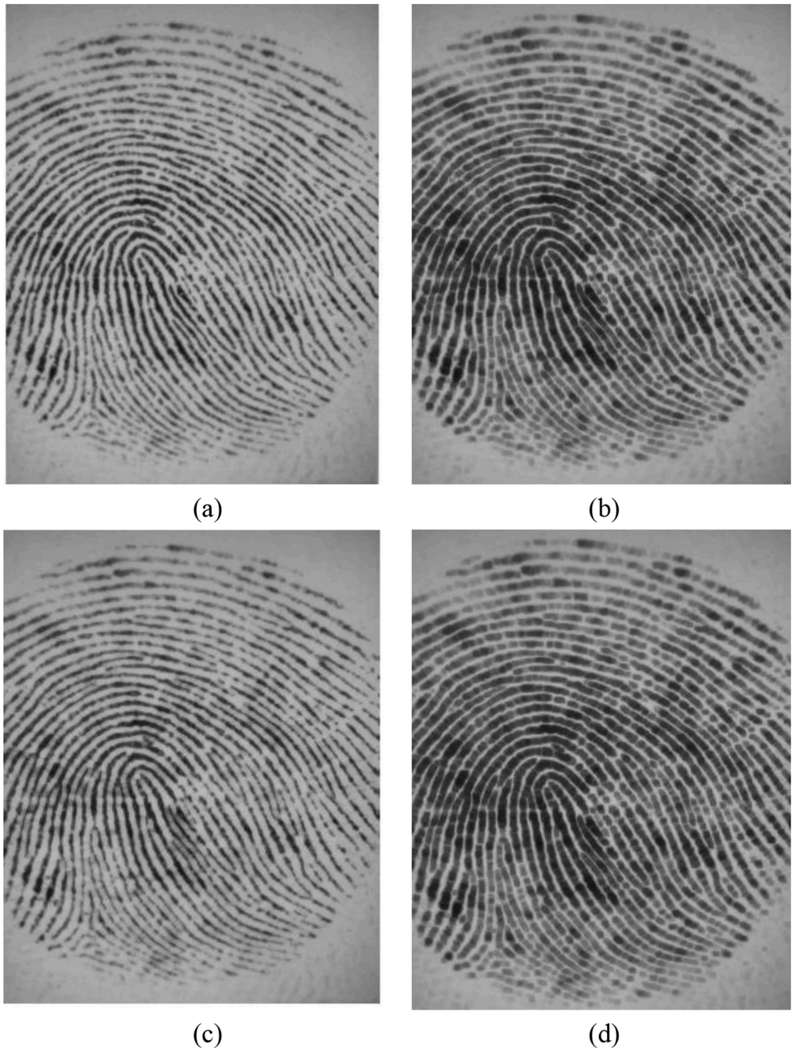

Fig. 2. Comparison of original image with preprocessed images: (a) Original image; (b) Dilated image; (c) Eroded image; (d) Opening of image.

Here, $x' = xcox\theta + ysin\theta$ and $y' = ycox\theta - xsin\theta$

This Gabor transform was implemented in the Gaussian envelope σ along the x and y directions. The spatial resolution was high if the value of σ was small and a low spatial resolution if σ was large. The features were obtained in the orientation θ along with the frequencies $f = \frac{x'}{l}$. The range of orientation is 0 to π. The proposed system calculated the co-occurrence matrix in four orientations ($\theta =$ 0°, 45°, 90° and 135°) to find the spatial relationship information. The symmetry was determined using the parameter ϕ. In different orientations, the Gabor filter was Centro-symmetric if $\phi = 0$, π and anti-Centro-symmetric if $\phi = -\pi/2$, $\pi/2$. In Fig. 4, Gabor filter are shown in different orientations and phases for high and low spatial resolutions.

In the literature, a number of statistical features for the image classification were found. However, in this study, four statistical features such as entropy, correlation, energy and homogeneity were considered. Finally, four statistical features for 16 metrics of different orientation, phase and spatial resolution were measured. Therefore, the feature vector contained 72 Gabor features for each fingerprint image.

2.4. Convolutional neural network (CNN)

CNN was used as a trainable deep neural network. The fingerprint image of size 227×227 pixels was used to extract the CNN features, which were used to train the CNN architecture. The structure consisted of a series of convoluted layers followed by a pooling layer. Each layer was defined for a specific computation. The designed network started with an input layer which indicated the size and type of the input data. The fully connected layer was the output layer, which used to perform the data classification. This proposed CNN architecture was constructed by the following layers.

Convolutional layers: The convolutional layer applied convolutional filters to the input images in this step. A set of mathematical

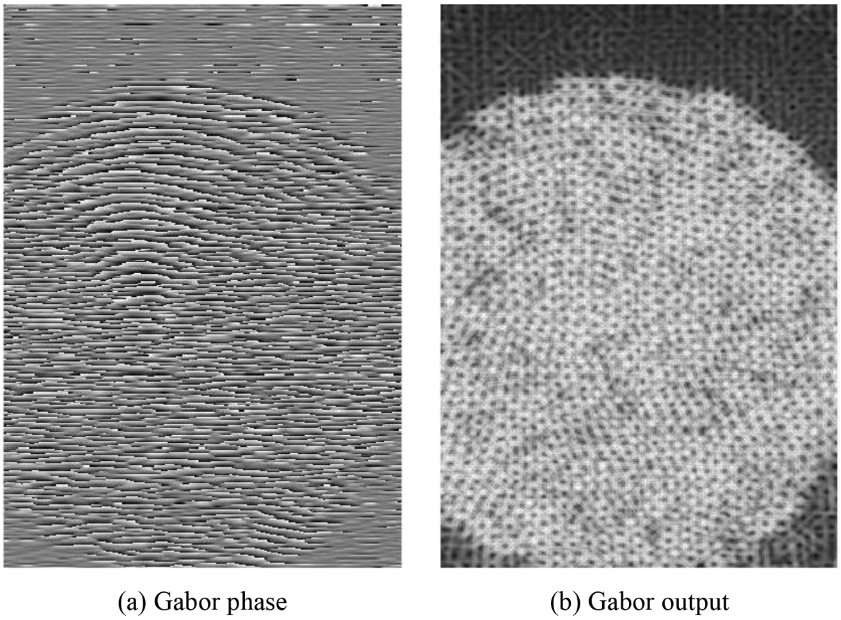

Fig. 3. (a) Gabor phase and (b) Gabor feature during extraction of textural information.

functions was performed on each image to produce a single value in the output feature map. The outputs were submitted to an activation function for introducing nonlinearities into the model. One of the most used activation functions used in this experiment was ReLU rectifier linear function, which can be mathematically expressed as, $\boldsymbol{f(x)}=\mathbf{max}\boldsymbol{(0,\ x)}$, where $\boldsymbol{x}$ is the neuron input. A smooth approximation to the rectifier is the analytic function, $\boldsymbol{f(x)}=\boldsymbol{ln(1+e\hat{\ }x)}$, which is also called the soft plus function.

Pooling layers. Pooling layer is another basic part in the CNN architecture. This layer summarised the features within a feature map extracted by the convolution layer using the average function or max-pooling, which were used to reduce the dimensions of the feature map. Therefore, the network had to learn reduced number of parameters and subsequently reduced the computational time. Max pooling algorithm extracted subregions of the feature map and keeps only their maximum value.

Fully connected layers. Classification was performed by this layer on the features extracted by the convolutional layers and down-sampled by the pooling layers. In this layer, every node is fully connected to all activations in the preceding layer. The CNN architecture containing layers, parameters and functions is graphically illustrated in Fig. 5.

Input layer: It takes the preprocessed fingerprint image. An image size of 227×227 where width 227 pixel and height 227 pixel was considered for this layer.

Two combination of convolutional and pooling layers: First convolutional layer contained padding 0 and a stride of 4, with a total of 96 filters having a size of 11×11. On the other hand, the second convolutional layer contained 256 filters of size 5 × 5, padding 2 and stride 1. Both layers were followed by a ReLU rectifier function. A max-pooling layer having window with a size of 3 × 3 and stride 2 was placed after each convolutional layer.

Three convolutional layers and a pooling layer: The third, fourth and fifth convolutional layers were followed by ReLU function containing 384, 384, 256 filters respectively. A max pooling layer with a size of 3 × 3 and stride 2 was arranged after the three convolutional layers.

Fully connected layer and an output layer: Among the three fully connected layers, first and second layers contained 4096 neurons each. The output layer denoted by the third fully connected layer could be triggered by a Softmax regression function.

Each layer of a CNN produced a response, or activation, to an input image. However, only a few layers within a CNN were suitable for image feature extraction. The layers at the beginning of the network captured basic image features, such as edges and blobs, which were subsequently processed by the deeper network layers combining the early features to form a higher-level image feature. Recognition tasks can be made easier by the higher-level features as they combined all the primitive features into a richer image representation. In the proposed system, the features were gathered from the fully connected layer 2.

2.5. Feature fusion

Gabor filtering techniques extracted feature from each fingerprint image and contained one vector with a size of 1 × 72. Similarly, CNN based feature extractor technique was applied to extract the features with size of 1 × 4096. The two vectors with the same format are concatenated in one fused vector. Features extracted by Gabor filter and CNN are represented by Eq. (4) and Eq. (5). The extracted feature vectors were then combined and represented by Eq. (6).

$$f_{Gabor\_Filter\ 1xn}=\{\ GABOR\_Filter_{1x1}, GABOR\_Filter_{1x2},\ GABOR\_Filter_{1x3}\ldots\ldots\ldots\ldots GABOR\_Filter_{1xn}\}\tag{4}$$

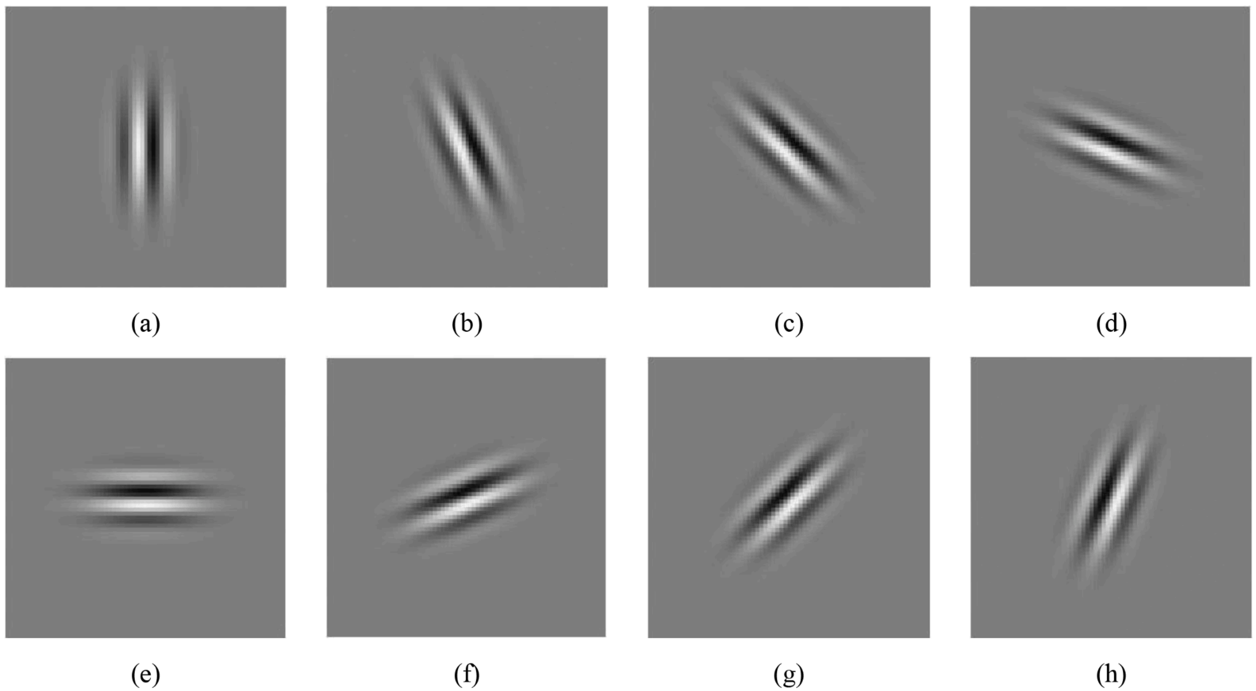

Fig. 4. Representation of Gabor filter for different orientation values and phases (a) 0, (b) $\pi/12$, (c) $\pi/6$, (d) $\pi/4$, (e) $\pi/2$, (f) $3\pi/2$, (g) $7\pi/12$, (h) $3\pi/4$.

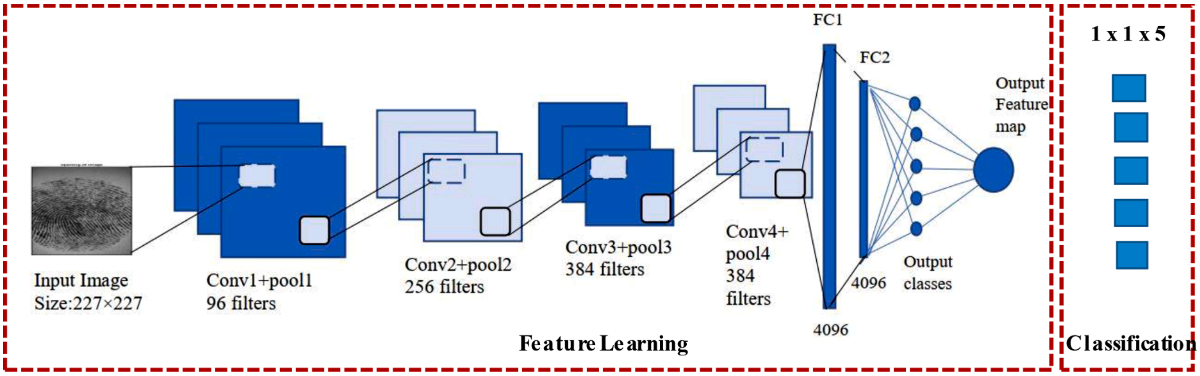

Fig. 5. The graphical illustration of the proposed CNN architecture.

$$f_{CNN\_AlexNet\ 1xm} = \{\ CNN\_AlexNet_{1x1},\ CNN\_Alexnet_{1x2},\ CNN\_Alexnet_{1x3}\ldots\ldots\ldots\ldots\ldots CNN\_Alexnet_{1xm}\} \tag{5}$$

$$Fused\ (features\ vector)^{cat}_{1\times q} = =\ \{f_{Gabor\_Filter\ 1\times n},\ f_{CNN\_AlexNet\ 1\times m}\} \tag{6}$$

2.6. Dimensionality reduction using PCA

A dimensionality reduction technique was applied on the fusion of feature maps before the classification segment. Principle component analysis is the most popular methods used mainly for dimensionality reduction in recognition problem to extract the region of interest (ROI) features. This is done by the removal of redundant and unwanted data economically. PCA is employed to map data from a high dimensional space to a low dimensional space by a mathematical procedure using its linear transformation [20]. The procedure is defined by the Eigen vectors of the covariance matrix. Let, N be the number of image and they are I1, I2, I1, . . ., IN. If the column vector is x_i, the mean of image pixels is given by Eq. (7).

$$\bar{x} = \sum_{i=1}^{N} \frac{x_i}{N} \tag{7}$$

Again, the projection space is defined by $X = x_i - \bar{x}$, made up of the Eigenvectors which correspond to the significant Eigenvalues and dimension is $M \times N$. The covariance matrix can be determined by Eq. (8).

$$C = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})^T = XX^T \tag{8}$$

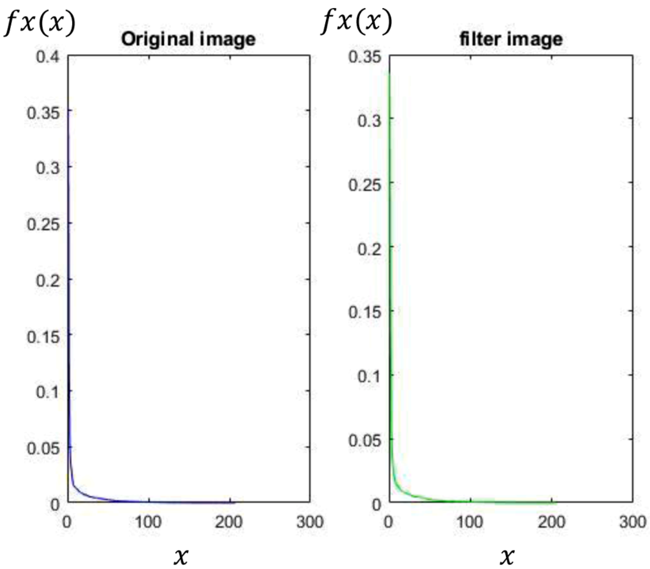

Fig. 6. Obtaining principle component from the fusion.

Here, $X = [x_1 - \overline{x},\ x_2 - \overline{x},\ x_3 - \overline{x},\ \ldots,\ x_N - \overline{x}]$. The rank of matrix X is N and X can be decomposed as Eq. (9).

$$X = U A^{\frac{1}{2}}\ V^T \tag{9}$$

A is the set of all nonzero Eigenvalues where $A = [\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_N]$ and $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_N$. $U = [u_1, u_2, u_3, \ldots, u_M]$ and $V = [v_1, v_2, v_3, \ldots, v_N]$ are two orthogonal matrix and $u_i$is the eigenvector of XX^T, $v_i$is the eigenvector of $X^T X$. For a corresponding eigenvalue λ_i the following relationship can be obtained (Eq. (10)).

$$u_i = \frac{1}{\sqrt{\lambda_1}} X v_1 \tag{10}$$

Where $i = 1, 2, 3, \ldots N$. Eq. (10) is used to form the Eigen image where PCA reduces the significant dimension of data maintaining the maximum possible variance. The fingerprint image belongs to the same category may differ in lighting condition, noise etc. However, some common patterns may exist referred as principle component. The Eigen image can be formed using these extracted principle components. Any original image can be reconstructed using the combination of Eigen images. Fig. 6 shows a comparison of the probability density curves between the original features and dimension reduced features after using PCA. Here *f(x)* represents probability intensity value and *x* represents mean of the intensity value. Probability density function was applied to check if there was a large amount of feature or information lost during filtering. In the case, when huge information of the features was lost, the curves would look significantly different from each other. It was observed that the probability density curves for both the original and filtered images were nearly the same This indicated that no significant features or information of the images were lost when fingerprint images were filtered or the information deviation was minimal in the filtered image compared to the original image.

2.7. Fingerprint classification and recognition

In this investigation, a multiclass classification method was applied, and a classifier was trained using the training data. Arch, Left-loop, Right-loop, Tented Arch, Whorl were considered as the different class levels. Although different classification methods like K-

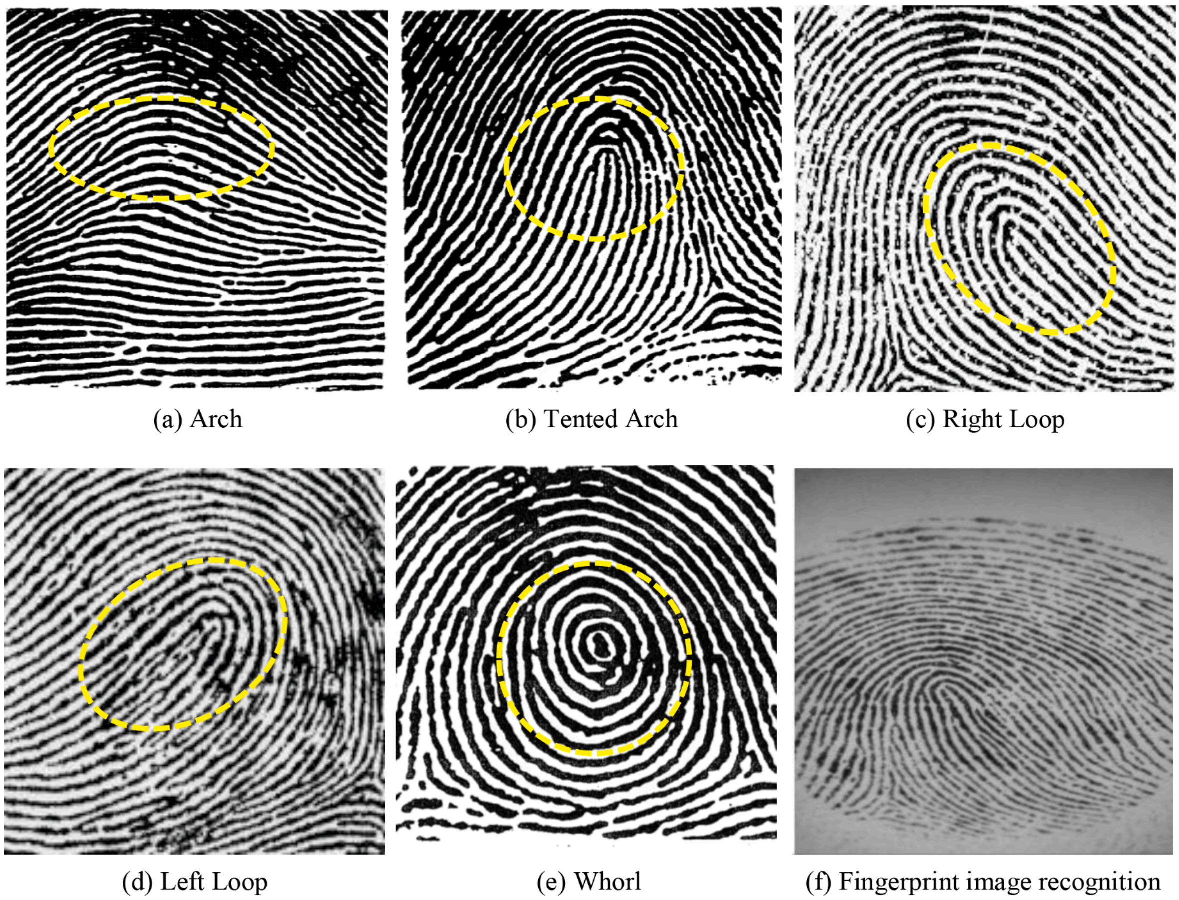

Fig. 7. Output segment for fingerprint class detection: (a) Arch, (b) Tented Arch, (c) Right Loop, (d) Left Loop, (e) Whorl, and (f) Fingerprint image detection.

nearest Neighbour (KNN), decision tree (DT), multiclass Support Vector Machine (SVM), are available, CNN classifier was employed due to its ability to produce classification with good accuracy. From the fingerprint dataset, image classes were extracted and divided into training and test datasets. Gabor features and CNN features were extracted from the five classes of fingerprint images. Each image generated 72 Gabor features and 4096 CNN features which were fused together to generate the input feature vector for training in the CNN classifier.

The classifier generated decision after training, on which class the image is belonged to using the features extracted from an input image. While the image class was detected, it was inserted into the feature map database and matched the desired person's fingerprint. If the person cannot be detected with the fingerprint, the system considers another input and continue detection as shown in Fig. 1. For a new person's entry, the sample fingerprints were also added to the feature map database and categorize according to the given class. The proposed recognition system is a fast and efficient approach as the recognition is performed according to the categorised classes.

2.8. Output window

The output of classification segment was processed to show the fingerprint class and detected sign. Afterwards, it was added to the feature map database and produced the output similar to what are presented in Fig. 7(a) to Fig. 7(e). At this point, score values of each ROI given by the CNN was assessed. Once the regions with higher scores are observed, their positions are averaged to find the final marker. If the system fails to detect, it starts processing the next input. An illustration of output fingerprint detection is presented in Fig. 7(f).

3. Experimental details

A good feature selection is an important aspect for the successful data analysis of computer aided video/image. The standard data accessibility is a vital issue for this investigation. The performance of any image classification is depended on the training dataset. Considering these factors, this investigation used approximately 9000 fingerprint images to obtain a satisfactory result. Table 1 provides the details of the datasets used with different fingerprint types for the experimentation.

In this proposed approach, the dataset was divided into training and test datasets. The 9000 fingerprint images were divided into 7000 for the training and 2000 for the validation. The features were extracted from the training dataset using the CNN and Gabor filter. A dimensionality reduction technique was applied on the fusion of those features. The CNN classifier was trained with the fusion of the extracted features. The features were extracted and passed through the classifier when the fingerprint was loaded into the system to perform the test. The decision was made based on the classification result whether it was valid or not. As soon as new data is added into the system, the features are used to train the classifier. Performance was evaluated by measuring sensitivity, precision accuracy, specificity, and F measure Eqs. (11) to (15) where TP denotes true positive, TN is true negative, FP indicates false positive and FN is false negative. The overall effectiveness of the classifier is measured by the classification accuracy. Specificity is a measure of effectiveness to identify the negative level of data using the classifier. The positive levels of data compared with the result of classifier are estimated by the F-measure.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{11}$$

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{13}$$

$$Specificity = \frac{TN}{TN + FP} \tag{14}$$

$$F - Measure = \frac{2 * (Sensitivity * Precision)}{Sensitivity + Precision} \tag{15}$$

A computer with the following specification was employed to perform all the training and testing: 64-bit Windows, 8 GB RAM, Intel Core i5 CPU, processing speed of 2.60 GHz. The times were computed on a Windows operating system computer with a GEFORCE RTX

Table 1
Fingerprint image categories with number of datasets.

Fingerprint type	Number of images
Arch	1760
Right Loop	2080
Left Loop	1640
Tented	2000
Whorl	1400

2070 super GPU. The system took 43 s to extract the feature using Gabor filter whereas 1.5 min for conducting the CNN based feature extraction. Then the features were fused by 0.13 ms. The training time and image classification time were recorded as 4 min and 0.87 ms.

4. Results and discussions

4.1. Performance evaluation and comparison with other methods

For the meaningful performance evaluation, several other fingerprint classification techniques such as k-Nearest Neighbor (KNN) [21], Decision Tree (DT) [22], Support Vector machine (SVM) and Random Forest (RF) [23] were tested against the proposed deep learning approach. KNN is a top-down approach where the classification was performed by building a decision tree from the training set. The maximum difference in entropy for the nodes was used to split the data. In KNN approach, the classification was determined by the distance metric and the value of k. The KNN for the test instance was computed and most frequent classes among these neighbors were returned.

The evaluation metrics including precision, sensitivity, specificity, accuracy and F-measure are projected for different classification systems in order to compare the performance against the proposed fusion system as shown in Fig. 8. From the comparison of the results it was evident that the proposed approach outperformed the other recent classification techniques for all metrices. For example, accuracy obtained by the CNN fusion approach was improved by 2.05%, 4.61%, 8.12% and 11.40% when compared to SVM, RF, KNN, and DT respectively. In terms of sensitivity, accuracy and F measure, SVM appeared to be the second best compared to the other techniques. However, in terms of precision and specificity, KNN produced the second best results. DT produced the worst results except in terms of precision where DT produced better results than RF.

The values of all the evaluation metrices obtained by the proposed method were close to 99% or higher. The higher accuracy obtained could be attributed to the fusion approach with the capability extracting better features. This meant that the probability of accurately identifying the fingerprints with this approach would be much higher. Gabor filter uses linear filtration and helps finding edges of objects with diverse frequencies, sizes, and directions, which perform identification and recognition of the biometric images to obtain better quality metrics. One-time filtration of Gabor filter has significant impact in reducing processing time of a biometric image [3].

The accuracy of classification obtained using the SVM and RF were 97.86% and 95.47% and these values were lower than the accuracy obtained by the CNN (99.87%). It's difficult to parallelize in SVM [24] but the CNN architecture inherently support parallelization. Furthermore, CNN compares the image piece by piece for matching similarity rather than whole image matching scheme and this can improve the classification accuracy. RF works better when the data is structured [23] but when the data is huge and mostly unstructured then the CNN classifier produces better results [25].

Accuracy vs. Epoch curve for the CNN approach is presented in Fig. 9. This showed an indication that no overfitting was found

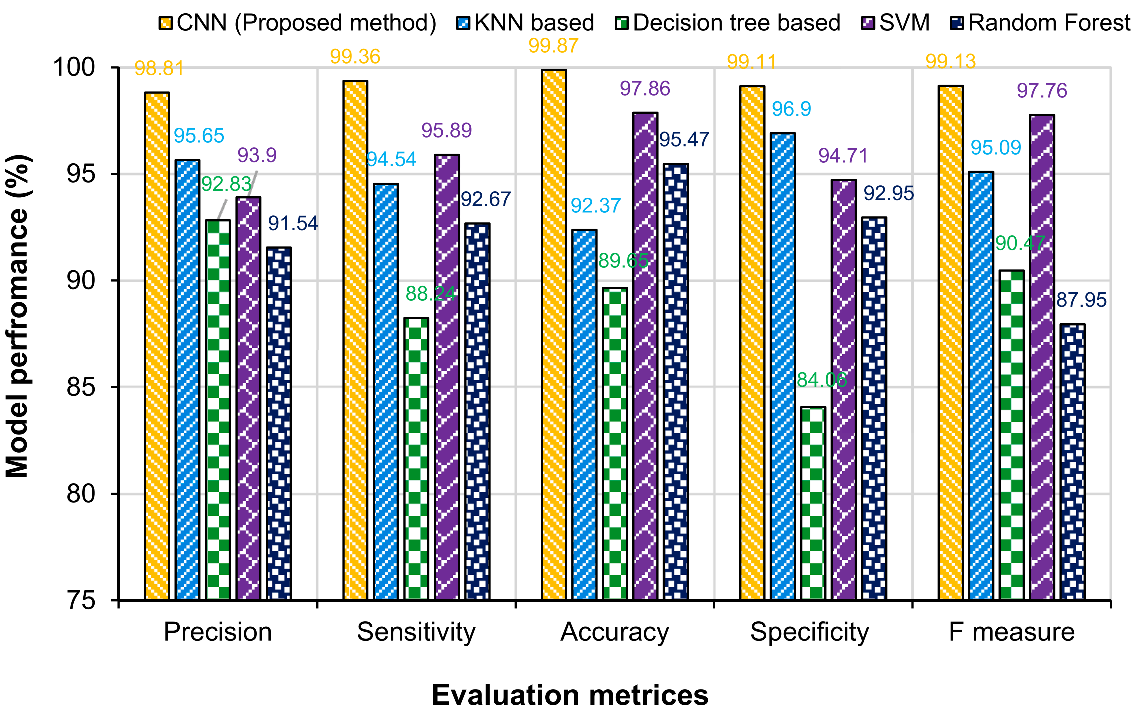

Fig. 8. Graphical comparison of evaluation metrices attained by the proposed system and existing classifiers.

during training and obtaining accuracy curves. The learning rate begins from 0.001 with mini-batch size 64 and 5 epochs. The loss curve indicated only a small amount of loss value.

Table 2 presents a comparison of accuracies between this work and other work in the literature. The proposed system could recognize features from a large fingerprint database using an automatic feature extraction and the CNN classification could achieved much higher accuracy than the other reported values. This can be attributed to the fusion approach applied where two techniques extracted different features within the images and combined to obtain additional features, which was not possible by one single technique. The additional features helped to match a fingerprint image with better accuracy.

Machine learning is applied on many applications for classification purposes. More recently, it was shown that CNN could successfully identify real fingerprint patterns from a six-category fingerprint database, which was annotated manually [33]. The new CNN model could achieve an accuracy of 94.87%, which was lower than the accuracy values obtained in this work. Furthermore, for images that have more diversity such as the fingerprint images, transfer learning method cannot extract features accurately compared to the AlexNet model.

Small area fingerprint containing less minutia is challenging compared to the traditional large area fingerprint recognition based on minutiae matching. Recently, Gabor filter was used to extract fingerprint dimension feature map as multidimensional feature extension named ROIFE_CNN, which was used as training image [34]. ROIFE_CNN algorithm was employed to classify and recognize the image through considering the center block of fingerprint as the region of interest (ROI). The authors claimed that feature extraction by Gabor filter and CNN classification could enhance the accuracy of fingerprint classification. However, they used one technique to extract feature and did not carry out any feature fusion. The application of feature fusion and PCA technique used in this proposed system improved finger recognition accuracy compared to other techniques.

Not many studies were found in the literature on fingerprint classification using fusion technique. However, Zhong et al. conducted a study on handwritten Chinese character recognition (HCCR) using a fusion approach combined with Gabor or gradient feature maps and HCCR-GoogLeNet [35]. It was shown that with the fusion of traditional directional feature maps, the proposed single and ensemble HCCR-GoogLeNet models could achieve a recognition accuracy of 96.35% and 96.74% respectively. This clearly indicated the effectives of using Gabor feature maps in further improving the performance of GoogLeNet for HCCR. However, in this proposed system, one fused feature vector was generated by extracting separate features by two techniques: Gabor and CNN. Gabor method can extract accurate features from image the edges. Furthermore, the application of PCA for dimensionality reduction of the extracted features also helped in achieving the better accuracy.

4.2. Miss classification using the proposed system

Based on the results obtained from this investigation, deep learning-based approach produced more accurate and reliable outcomes compared to other existing methods. The confusion matrix presented in Table 3 indicated the miss classification details. Confusing datasets could be responsible for the generation of a small number of miss classifications.

It should be noted that the proposed approach achieved 99.87% accuracy which corresponded to only 10 failures among 5000 test frames. Fig. 10 shows some wrongly detected fingerprint images. It was also clear from the results that the fingerprint class Arch was well differentiated by the system compared to the other classes as evidenced by the correct classification of all 901 Arch fingerprints.

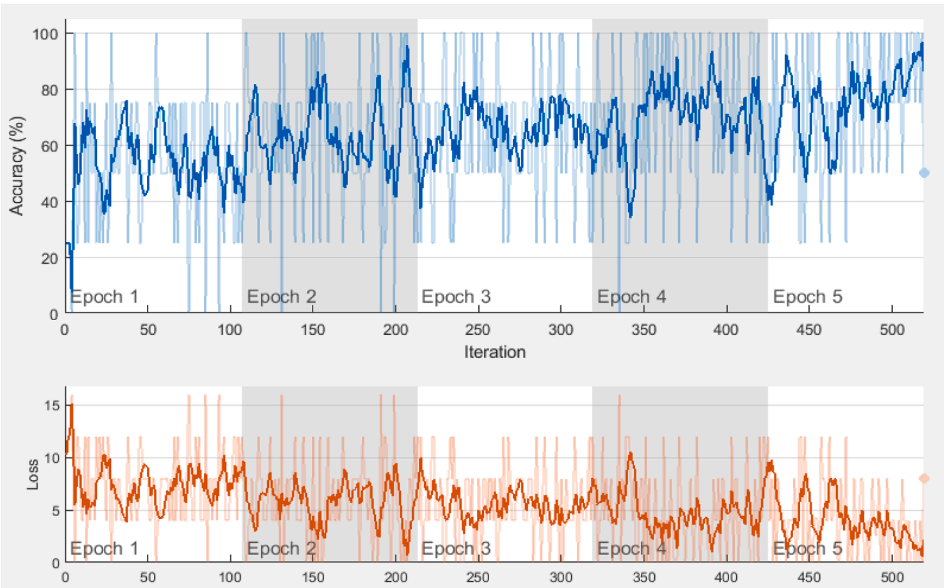

Fig. 9. Accuracy and Loss vs. Epoch for the learning curve based on CNN architecture.

Table 2
Comparison of fingerprint classification accuracies.

References	Fingerprint classification technique	Accuracy (%)
Nguyen [23]	Random Forest (RF) + CNN	96.75
Yang et al. [26]	ROIFE_CNN on Gabor filtering image of ROI	95.10
Michelsanti [27]	CNN	96.01
Everingham [28]	Decision trees	98.00
Hong [29]	SVM algorithm + naive Bayes method	95.60
Strobl [30]	Random Forest algorithm	96.50
Cristianini [31]	Support Vector Machine (SVM)	94.97
Mohamed [32]	Fuzzy-neural network classifier	98.00
Proposed System	Fusion of CNN and Gabor features	99.87

Left loop was somehow overlapped by the Tented and Whorl classes whereas the Right loop was wrongly assigned to the Tented class. The Tented class was overlapped by the Left loop and the Whorl was overlapped by the Left loop and the Right loop. However, the failure rate of less than 1% proved the real success of this fusion based classification approach for identifying fingerprint in practical applications.

4.3. *Further validation and analysis*

Further validations were carried out by K-fold cross validation and generalization techniques and compared their accuracies with the proposed method. In the k-fold cross validation technique, average recognition accuracy was computed by applying various k-folds for all the classifiers. Features vector set was split into k equal subsets. k-1 subsets were employed for the training while retaining a single set for the testing. The process was repeated k times (k-folds), with each of the k subsets considered for testing. Afterwards, the k estimations from the k-folds were averaged to prepare a final predictable value. In this case, the classifiers were trained by a 10-fold cross validation. In this step, the feature vectors were randomly divided into 10 sub folds. Nine sub folds were selected from the training dataset and one single sub fold from the testing dataset. Fig. 11 illustrates the characteristics of the five classifiers applied in the experiment. Generally, the accuracy of the decision tree (DT) classifier was influenced when less training data was employed. At the same time, CNN classifier achieved the highest recognition rate using small training set (i.e. 2-folds) among the classifiers. On the other hand, KNN, SVM and RF classifiers achieved medium level of accuracy.

The experiments on mean accuracy, loss of training and testing in the 10-fold cross-validation have been conducted and presented in Fig. 12. It is found that the training accuracy was higher than the test accuracy.

The generalization accuracy of majority of the published work using fingerprint images is not satisfactory. Therefore, the proposed system used standard dataset for generalization to achieve a better accuracy. In generalization, 4000 images with five classes of image were used and an of accuracy of 97.75% was achieved with minimum wrong detection rate. Fig. 13 shows the comparison of measurement accuracies with different approaches used in this study. K-fold validation technique produced a better accuracy of 98.56% compared to the accuracy (97.75%) obtained by applying the generalization method. However, the proposed approach produced the best accuracy of 99.87%. Therefore, this comparison demonstrated the robustness of the proposed systems with high accuracy of fingerprint matching.

The proposed system works effectively to identify fingerprint images and provides high accuracy, which is confirmed by generalization and K-fold validation techniques. In generalization, a completely different dataset was used, and high accuracy confirmed that the system would identify fingerprint images accurately in an unknown situation. In the k-fold cross validation technique, average recognition accuracy was computed by applying various k-folds for all the classifiers. Higher accuracy obtained in k-fold validation further confirmed that the proposed system could higher matching accuracy in practical applications. Furthermore, the models developed based on a large data set (9000) contributed toward ensuring the robustness of the entire system.

Dilation continuously fills the missing pixel of a broken ridge as it can add pixels at the boundary of the objects. By applying this operation, the object enlarges its regions, shrinks the single hole, and reduces the gap between two regions. Erosion can be used to remove the noisy connections between two objects. The effect will be sharpened fingerprint image since the unwanted pixels are excluded. However, dilation-erosion technique suffers from limitations such computational complexity, longer computation time, and possibility of losing essential pixel areas. Adaptive morphological operation was suggested to overcome the issues and improve filtering performance [36]. Furthermore, Deep Neural Network (DNN) could be used for filtering fingerprint images. Bae et al. [37] proposed a new CNN model based on FusionNet for fingerprint denoising and inpainting. The proposed model demonstrated very good performance in semantic image segmentation. However, this was not be compared with the traditional dilation and erosion process. In addition, Biswas et al. [38] reported that CNN techniques could not produce accurate image segmentation and add additional noise owing to the limited receptive field of the convolutional filters. They proposed dilated convolutional filtering technique to obtain a larger receptive field, which would help in achieving better accuracy in the image segmentation. In future, these techniques will be further explored to improve the accuracy and soundness of the proposed system.

Conclusions

Fingerprint is the most commonly used human feature in automatic detection of authenticity which deals with a very large number

Table 3
Confusion matrix of the proposed system.

True class	Predicted class Arch	Left Loop	Right Loop	Tented	Whorl
Arch	901	0	0	0	0
Left Loop	0	844	0	1	1
Right Loop	0	0	1048	2	0
Tented	0	3	0	1142	0
Whorl	0	1	2	0	1050

Fig. 10. Examples of miss classification of fingerprint class by the proposed system.

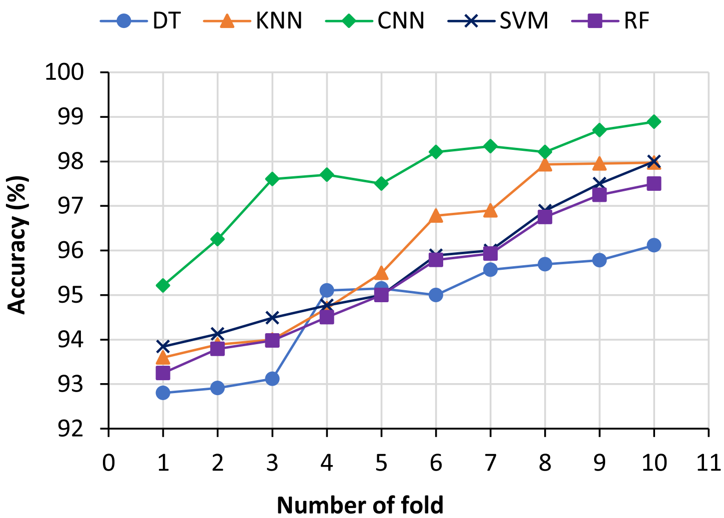

Fig. 11. Comparison of the achieved average accuracy of different classifier.

of databases. A high accuracy rate is very crucial in the classification and detection of fingerprints. The traditional feature extractors and classifiers are only able to increase the accuracy to a certain extent. This paper has presented a novel deep learning-based study to reduce the fingerprint rejection rate and increase the performance of evaluation metrics. The strength of Gabor features and the power of convolutional neural network (CNN) features were used to form a novel fusion of feature map, which was an important contribution in developing this intelligence system. The dimensionality reduction algorithm (PCA) was applied on the feature map to get better accuracy. The proposed technique produced an accuracy of 99.87%, which was higher than other state of the art classification techniques. The technique was also validated by k-fold (98.89%) and generalization (97.75%), which showed slightly lower accuracy. Therefore, a failure rate of less than 1% has demonstrated a significant success of the proposed fusion based approach in accurate fingerprint identification.

Author statement

All authors have equal contribution to prepare and finalize the manuscript.

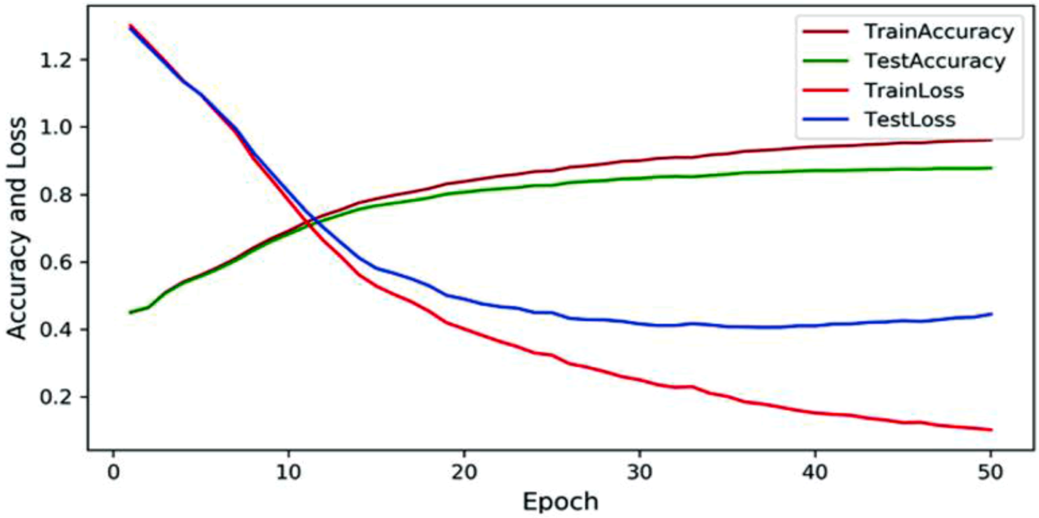

Fig. 12. Mean of 10-fold cross validation accuracy and loss of train and test.

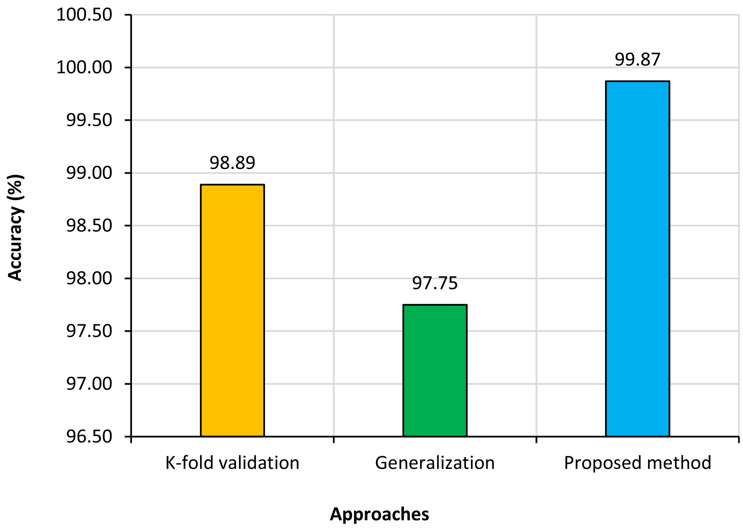

Fig. 13. Comparison study of accuracy with different approaches.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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