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An Efficient Real-Time Ear Biometric System Using Deep- Learning

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Abstract **Biometric system has certain unique features which can be used to distinguish people from each other and makes the security robust. People can be easily distinguishable using ear images for the reason being ears can be easily captured from the distance making it appropriate for applications like cybercrimes and surveillance. In this paper, real-time ear recognition system has been proposed which uses convolutional neural network and viola-jones algorithm for ear recognition. The system GUI provides two options of that are training and testing separately. The training GUI enrolls the new users account into the database along with the system training with IIT-Delhi ear dataset. The testing GUI is used to check the efficiency of the system. The algorithm utilizes eleven layers of convolutional neural network along with viola-jones algorithm for achieving a good recognition rate with small size of data too.**

Keywords —Ear, ear biometrics, deep learning, machine learning, computer vision.

I. INTRODUCTION

To distinct a person from other person is a big challenge. Traditionally, there are many methods which are being adopted such as passwords, keys, smart cards, magnetic cards [1] but all are in vain when it comes to identification and authentication via Biometrics.

Biometrics is a scientific method that is opted to distinguish a person automatically by using their physical and (or) biological traits. These characteristics according to study should be unique and not duplicable or transferrable [1] hence it becomes a better option from the formally mentioned methods which are easy to lose & forget. Biometric has several uses that includes authentication at workstations, transactions from bank, granting access to authentic person, cyber-crimes and surveillance.

Based on whether it requires human contact or not biometric is broadly classified into two categories- one that requires touch is called as invasive (active) biometrics and other that does not require touch is called as non-invasive (passive) biometrics. The active biometrics includes fingerprint and signature whereas passive biometrics includes ear, face and gait.

Many biometric systems have been accepted but ear an unenlightened biometric is still in research and is narrowly used. People are still in slumber and unfamiliar about ear biometrics. It has been researched that ears are also distinguishable just like faces in the study of Iannarelli [2]. It has advantage over other biometrics systems which are discussed below:

1) **In comparison with Face Recognition system**
   Ear being smaller in size has advantage over face in a way that its computational load is small. Also, it has been seen that ear has uniform colour whereas the colour of the face varies drastically across cultures and over time.

2) **In comparison with Fingerprint recognition system**
   Fingerprint is smaller than ear size but ear recognition system is contactless which has the benefit of saving cost for installation of touch sensors. Thus, reducing the chance of harming the recognition system as well as any possibility of spreading contiguous disease is avoided.

3) **In comparison with Iris Recognition System**
   Ear Recognition System takes over Iris Recognition System for the reason being they work with normal cameras. Iris recognition system also gives low recognition when one wears glasses. Also, high quality laser sensor scanners are required which costs a lot.

The principle of biometric systems works on the collection of data, performing feature extraction & then classifying data based on that. Since feature extraction is one big tedious task, researchers found that artificial intelligence can unravel this job by enabling machines to mimic human behaviour.

Artificial intelligence works on two sides of coin i.e. machine learning and deep learning. Machine learning takes features manually whereas deep learning automatically identifies features by using artificial neural network. Based on that features, artificial neural network is trained. Later same model is used for testing the new dataset and hence classifying the required data. There are several more advantages which include better accuracy results and testing

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also takes less time making preferable to use in image processing.

The rest of the paper is organised as follows. Section II represents literature work of related area. Section III describes the proposed methodology for ear biometric recognition system. Results are discussed in Section IV. Section V concludes the paper followed by references.

II. State-Of-The-Art

Liang Tian et. al [3] designed a convolutional neural network for ear recognition. In their work they have created a CNN model consisting of an input layer, 3 convolutional layers, 3 pooling layers and 2 fully connected layers. For classification of ears softmax classifier is used. They have experimented on USTB III ear dataset that includes 79 subjects. The average accuracy of their model was 98.27%.

Samuel Dodge et. al [4] proposes method for ear recognition using deep neural network. The problem of over fitting is also discussed which can be removed by using pre-trained deep neural networks (DNNs) with shallow classifier. They have compared 5 state-of-the-art DNNs, namely, AlexNet, VGG16, VGG19, RESNet18 and RESNet50 out of which RESNet18 model gives the best results as the model has few parameters.

Fevziye Iren Eyiokur et. al [5] applied the concept of domain adaptation on pre-trained CNN models, trained on ImageNet dataset. They have evaluated the performance of deep CNN models namely AlexNet, VGG-16, and GoogleNet on two datasets that are UERC dataset (Unconstrained Ear Recognition Challenge) & their own collected multi-PIE ear dataset. They have calculated the accuracy of the models and evaluated that by combining CNN models it has increased by 4% whereas when domain adaptation is applied it has increased around 10%. Also, it has been observed that performance is increased when data augmentation is applied whereas no change is seen when alignment is applied.

Yi Zhang et. al [6] fine-tuned some popular pre-trained deep CNN Models: Alexnet, GoogleNet, VGG-16, ResNet101, and VGG-Face on the images of USTB-Hello ears which are under uncontrolled conditions like lighting, pose variations and occlusions. The experiment shows that VGG-Face deep model obtained the best results. These deep models were further modified by replacing last pooling layer with SPP layers.

Ting-YuFan et. al [7] detected human faces and ear using faster R-CNN. Further CNNs are trained using those detected images of ear and face. Finally, Bayesian decision fusion method is applied to fuse and improve the recognition results. Their CNN Model achieved 93.4 % accuracy in recognizing human by using both face and ear together as features.

Tiang Ying et. al [8] proposed ear recognition based on deep convolutional neural network. They have analyzed their algorithm when rotation and occlusion is applied and experiments shows that accuracy is above 90% when 0% to 30% of occlusion is there whereas within 30-degree rotation angle recognition rate is 98%.

Rizhin Nuree Othman et. al [9] proposed a novel approach for ear recognition when they are partly occluded. For ear detection they have used haar feature- based cascade technique. The features of ear are described by shape context computation. The similarity is calculated using Chi-squared values. The pitfall of this paper is that 57% of recognition rate is achieved when ear is partly occluded.

Salman Mohammad Jiddah et. al [10] applied both geometric as well as texture features in recognition of ear. The experiment was conducted on AMI ear database. For geometric feature extraction Local Binary Pattern (LBP) is used and for texture feature extraction laplacian filter is used. After that histogram extraction technique is applied on both geometric as well as texture features and resulted histograms are fused together. For classification K-nearest neighbor classifier is used (KNN). The results show that accuracy is 70% when LBP is applied & 69 % when laplacian filter is applied. It reduces drastically to 56% when fusion of both techniques is applied.

III. Proposed Methodology

The proposed real time ear authentication system consists of following steps:

1. Acquisition of ear and dataset creation.
2. Training of dataset created.
3. Real time testing.

The proposed flow diagram is shown in Figure 1:

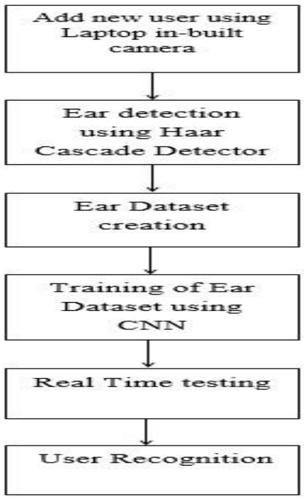

Figure 1: Flowchart of Proposed Ear Recognition System

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A. Image Capturing and Ear Detection

The side face image is captured using laptop camera and pre-processing of image is done. The pre-processing step involves image greyscale conversion and resizing of image size. Later on, viola-jones algorithm is applied to extract ear from the face image. It uses haar cascade-based features for detecting ear part from a face image. Histogram of equalization is applied on the detected ear for enhancing the visual quality and further it is resized to 28x28 pixels image size.

B. Training

Training is done using convolutional neural network consisting of 11 layers. For training of the system, we have used IIT- Delhi 2D ear dataset along with our dataset of 10 subjects. The new dataset created by us follows same standards of IIT-Delhi ear dataset. The explanation of CNN architecture is as follow. The first layer is input layer. The detected ear of size 28x28 pixels is fed to the input layer of convolutional neural network. Second Layer is Convolution Layer which is made up of 16 filters of size of 3x3. The main purpose of this layer is to perform convolution operation to extract features of ear. Third layer is batch Normalization layer which normalizes each input for speeding up the training of convolutional neural network. After this layer, Rectified Linear Unit layer is used to introduce non-linearity to the network by performing element wise operation and setting all negative pixels to zero. To further reduce the dimensionality of input ear image, maximum pooling layer is used with pool size of 2x2 and stride of 2. Again, another convolution layer is applied made up of 32 filters of size 3x3, and batch normalization before a rectified linear unit layer. Lastly fully connected layer is used which updates the features till the best results are achieved to classify the ear images. Also, softmax layer and classification layers are used. The trained model achieves accuracy of 100%. Figure 2 shows the architecture of proposed CNN model.

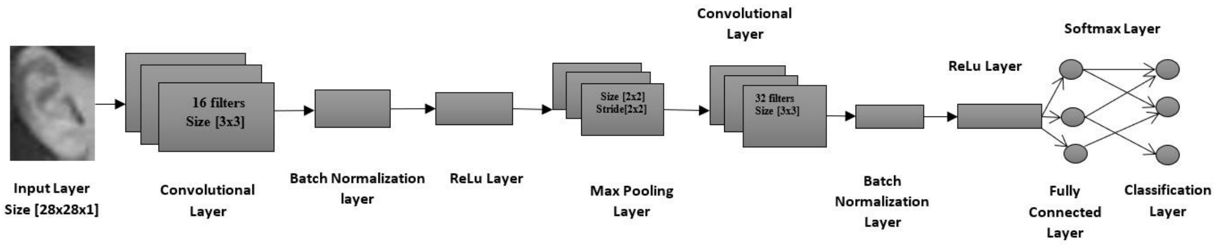

Figure 2: CNN Model Architecture

C. Testing

A good ear recognition system should identify the user by analysing unknown ear images (probe images) with the already present ear images in the enrolled dataset (gallery images). Testing is performed after the successful training of the Convolutional Neural Network. The training and testing are performed on MATLAB 2018a software on Windows 10 with Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz- 2.90GHz processor. For testing both options of selecting image from gallery or real-time ear capturing are provided to the operator in the GUI.

IV. RESULTS

A. Training Phase

The training accuracy and loss rate with 150 epoch for the dataset of IIT Delhi is shown in Figure 3. From the figure it can be seen that the accuracy reaches 100% after 60 iterations. The training of system takes 9 seconds. After 60 iterations, loss rate starts to decline and reaches below 10% after 140 iterations.

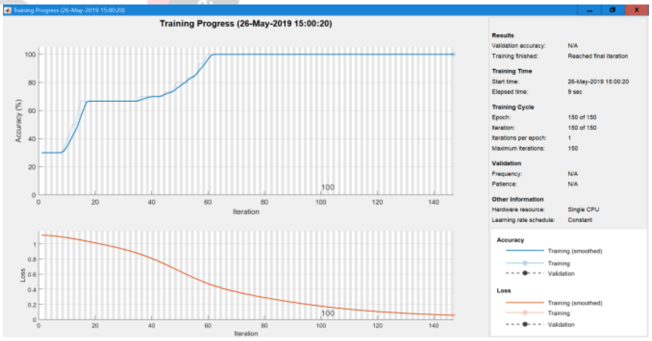

Figure 3: Accuracy and Loss Rate Value of Model

B. Testing Phase

The GUI for testing is shown in Figure 4 and 5. It provides two options for testing that are; testing the images stored in gallery or testing real-time images captured from laptop in-build camera. Figure 4 shows the results from gallery database whereas Figure 5 shows the testing results of real-time run. The run-time testing captures 10 shots in succession and select the most stable and visuality good quality image. The ear detection is done by haar features and features are extracted by the CNN architecture and are matched with the stored database.

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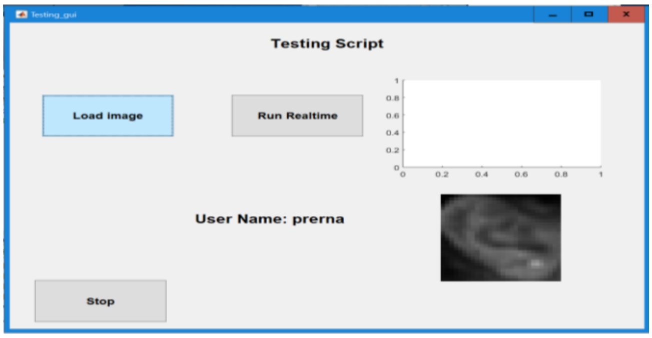

Figure 4: Testing Phase A

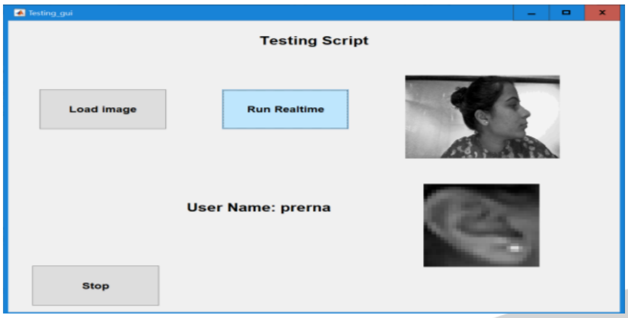

Figure 5: Testing Phase B

The implementation is done on MATLAB software using neural network and image processing toolbox. The GUI layer toolbox is used for creating the user graphic window for easy excess of code implementation.

V. Conclusion

In this paper, real-time ear recognition is performed using deep learning based Convolutional Neural Network. The ear extraction is done using viola-jones algorithm. The proposed approach uses haar cascade detector to detect the ear image from the face captured from the in-built laptop camera. The accuracy of the system is 98.9%. For training of CNN, IIT Delhi ear database along with our own database of 10 subjects were used. Overall execution time of processing is very fast and the system can be used for real-time biometric identification system. In the future, we plan to test our system on other databases.

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