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PERSON VEIN IDENTIFICATION USING CNN

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Abstract:

Security is one of the major concerns of current times. Biometric based methods are found to be more reliable and accurate in authenticating an individual. Hand-based biometric traits are proved to be easily accessible during data collection. Collecting, storing and processing biometric trait images of all the employees is always a challenge for larger organizations. Deep learning techniques come to rescue from such situations. In this paper, we propose a novel approach for authentication using finger-vein images. We use basic convolutional neural network (CNN) with transfer learning. The model has been pre-trained on various types of images available on ImageNet database through ResNet – 50 architecture. This pre-trained model has been then run through CNN model with appropriate number of hidden layers and activation functions. The optimizers and loss functions are used to achieve appropriate classification among the images. The simulation results of proposed model has shown 99.06% of accuracy in classifying an individual.

Introduction:

Functionality of human identification and authentication exists from the ancient days. As the crime rate increases, security is essential [1]. Hence, authentication of an individual was much required. Human identification and authentication can be done in two ways, viz. by using behavioral characteristics and by using physiological characteristics [2]. Behavioral characteristics such as voice, keystrokes, signature, gait, etc. are easy to forge and replace, hence such biometric systems can be easily getting spoofed. There are various physiological characteristics in use today such as finger print, knuckle print, palm veins, finger veins, face recognition and iris recognition. To achieve higher level efficiency, two or more traits also be combined. Pros and cons of various biometric traits are mentioned in the Table 1 [3]. Hand based biometrics such as palm veins and finger veins are attracting researchers in more numbers from past decades as they are easy to access,

highly accurate and impossible to replicate [5]. From the medical research it is proved that: 1) Every individual has a unique finger vein pattern,
2) For the same person, finger veins vary among his/her fingers, and 3) As the individual grows, their finger vein pattern will not change [3,4]. There are many outstanding advantages of finger vein features: 1)As every individual having unique finger vein pattern, it provides excellent clear cut dissimilarities between individuals. 2) Finger vein patterns are alive. 3) Finger vein pattern remains same and does not change with time. 4) It is almost impossible to forge, obfuscate or mutilate the finger vein pattern [3]. Despite advantages, there are some challenges and improvements to be done to attain elevated performance in the image acquisition device and efficient preprocessing techniques [3]. Biometric system based on finger vein works in four stages: image acquisition, image preprocessing, feature extraction and feature matching. Image acquisition can be done with help of near infrared light in two ways, light reflection method and light refraction method [6]. Usage of efficient image acquisition device is very crucial otherwise there will be too much of preprocessing to be done. Many existing finger vein recognition systems work well with neat and clean image. So, improvements are required even if image is not clear and if finger's position is perverted or depraved. Once vein image is obtained, it is necessary to preprocess it to enhance the image for better performance [7]. In finger vein biometric systems, feature extraction plays an important and critical role. Feature extraction methods are classified into three categories 1) dimensionality based 2) local binary based and 3) vein structure based. Extracted feature should be matched with the stored template. For this efficient matching algorithm is required. Since it is easy and efficient to make deep learning networks to learn the patterns, we are incorporating the concept of deep learning in the finger vein biometric system. There are many GPU accelerated deep learning frameworks to train the convolutional neutral networks [8]. From the past several years, striking advances in the field of deep learning and artificial intelligence results in exceptional high performance in image processing particularly by using deep convolutional neural network. Major innovation is that, it operates directly

on the raw image extracting the features from the acquired image, thus improves the time efficiency [9].

Literature Survey:

Generally, biometric systems involve four major steps viz image acquisition, image preprocessing, feature extraction and matching. In image preprocessing stage, many tasks are performed to enhance the quality of the image by doing noise removal, resizing, sharpening, identifying the region of interest, image enhancement, blurring, deblurring, etc. in feature extraction stage, image segmentation is done in order to get the finger vein information. Finally, extracted finger vein feature is matched against the stored template in order to authenticate. Syafeeza Ahmad Radzi et al [3] proposed finger vein biometric based on convolutional neural network which focused more on preprocessing and developing a CNN model. Segmentation is done by using local dynamic thresholding which results in lower computation complexity. CNN architecture is developed based on fused convolutional and subsampling layers. The proposed method tested on the samples from 50 and 81 subjects which is not sufficient to decide the robustness, efficiency and accuracy of the system. Hyung Gil Hong et al, [6] proposed finger vein recognition using convolutional neural networks in which ROI is identified based on upper and lower finger boundaries. Recognition of finger vein is done by pre-trained CNN model. This method requires much preprocessing tasks as it captures the finger vein image by using only six 850 nm near infrared LEDs. Rig Das et al [10] uses convolutional neural network for biometrical identification with the help of finger vein. They performed comprehensive set of experimental tests over four publicly available and commonly used databases. But requires improvement in the identification accuracy if finger vein images are not captured with the same illumination intensity and environmental lighting conditions. Mansur Mohamed Ali et al [11] proposed a finger vein recognition system with gray level co-occurrence matrix which works based on the discrete wavelet transform. The proposed method provides higher accuracy right if there is no flexibility in the distance between the finger and the camera and if there is no flexibility to rotate and translate. Iram Malik et al [12] uses repeated line tracking and gabor filter methods for human identification using finger vein pattern. Even though these two features are used to extract the features, they are combined these two approaches to increase the effectivity and reliability. By combining finger vein biometric with some other biometric techniques, higher accuracy can be achieved which are much essential for the security concerns in the sensitive areas. Huafeng Qin et al [13] uses deep learning model for finger vein verification. They segmented the vein pixels from the background pixels and recovers the missing vein patterns by predicting the probability of a pixel to belong to a vein pattern. For this, they used ample statistics on non linear pixel correlations, through a hierarchical feature representation using deep neural network. Also, CNN based scheme is used to instinctively learn features from the tender pixels in order to achieve finger vein verification. The trained CNN model will not be able to identify the vein pixel if it is characterized by the poor illumination. Wenjie Liu et al [14], proposed finger vein recognition system with the help of deep learning. In order to extract the region of interest, width and length of the finger vein is extracted by using compass operator. Five convolutional layers and two fully connected layers are used in the network architecture of CNN Model. Accuracy should be checked by running on the public database with a large quantity of data. K S Itqan et al [15] proposed a user identification system based on finger vein with the help of convolutional neural network. They emphasize more on the preprocessing and the CNN design. Four-layer CNN model is used which is derived by Lenet-5 architecture having smaller sized neural network. Subsampling layer and convolutional layers are fused and two fully connected lone nodes are used as a classifier. The proposed methodology has to be tested against the ginger vein real time system to know the accuracy.

Existing System:

Different approaches then used for Finger Vein using sliding window and region proposal algorithms. HOG (Histogram of oriented Gradient) models were used to predict the objects in the frame. HOG significant work used low-level features, discriminative learning, and pictorial structure along with SVM [35-37]. These algorithms were slow for real-time scenarios with 14s per image. Although these classifiers gave good accuracies, the slowness of the sliding window method was a big problem, especially for the real-time implementation purpose.

Disadvantages of Existing System:

Finger Vein in real-time is a very challenging task. As our desired object detecting it in an image is also very challenging in presence of other objects, especially those objects that can be confused with it. machine learning models faced several below mentioned challenges for detection and classification task: The first and main problem is the data through which

- Machine learning its features to be used later for classification and detection. No standard dataset was available for weapons.

For real-time scenarios, making a novel dataset

- manually was a very long and time-consuming process. Labeling the desired database is not an easy task, as
- dataset for one algorithm cannot be utilized for the other one. Every algorithm requires different labeling and preprocessing operations for the same-labeled database.
- As for real-time implementation, detection systems

Methodology:

As discussed, most of the researchers worked on neural networks approach for finger-vein authentication and/or identification have followed traditional CNN model. Basically, a CNN model requires a huge dataset so as to learn from the training dataset. The finger-vein database used in the proposed work is SDUMLA-FV built by Shandong University [17], which has finger-vein images of just 106 individuals. Hence, the proposed work has been implemented based on transfer learning model [18]. The transfer learning is an approach where the model is pre-trained on a huge database of images and the knowledge gained by the model through those images is used for training another set of images. One of the major transfer learning models is ResNet-50 [19] and the architecture of this model is shown in Figure 1. The proposed work aims to implement classification algorithm to classify 106 individuals based on their finger-vein images. Hence, this will be a multi-class classification problem with 106 different classes. The SDUMLA – FV database constituted with six images of each.

of index, middle and ring fingers of both left and right hands of an individual. Hence, there are totally 36 images for every person. The total number of images in the database would be 36*106 = 3816. The initial task is to put all these images into a single folder, without any distinction. This whole data set must be divided two parts: training set and testing set. Each of these sets must be again

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bifurcated as input and target. Here, the inputs are the images themselves and the target is the name of the class (0 to 105). With this initial setup, we must proceed for building the model. The architecture of the proposed work is shown in Figure 2. The proposed work follows various steps like flattening the image, model building etc. as discussed in the following sub-sections.

Proposed System:

The proposed algorithm is implemented using TensorFlow 2.0 with Keras [25]. The programming language used is Python 3.7. The GPU available with Google Colab [26] is used as the CNN requires a high RAM for execution. As discussed before, the image dataset has been divided into training and testing set with 3052 and 764 images respectively. When the model is trained and tested on these images, it stopped after 19 epochs. The values for training loss, training accuracy, validation loss and validation accuracy are briefed in Table 2. As the number of epochs increases, the accuracy increases and the loss decreases. But, the rate at which increase in accuracy and decrease in loss for training set and testing set will be different. The generalization performance of both sets with respect to accuracy and loss are given in Figure 4 and Figure 5. It is a customary to draw a confusion matrix for any classification problem. Here, we are dealing with 106 classes and hence the confusion matrix will be of order 106 * 106. As the representation of such a big matrix is almost impossible on a paper, it is not being included here. But, it is found that only one misclassification is resulted – the finger-vein image of person number 72 has been wrongly classified as person number 14. Thus, the proposed model has shown 99.06% of accuracy in authenticating the person.

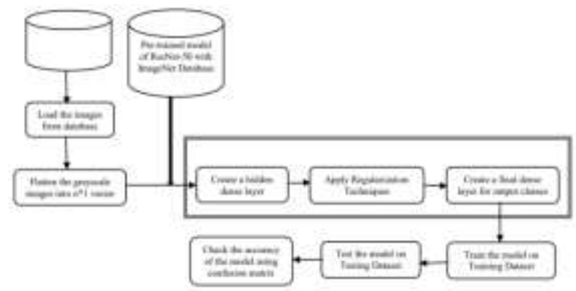


Figure 2: Architectural Diagram of the Proposed Work

Implementation

Flattening the Image The sample input grayscale images are shown in Figure 3. These images are of two-dimensional array (of m x n pixels) to a one-dimensional array (of mn x 1 pixels). Think of this layer as unstacking rows of pixels in the image and lining them up. This layer has no parameters to learn; it only reformats the data.

2) REGION PROPOSAL/OBJECT DETECTION MODELS Dense Layer

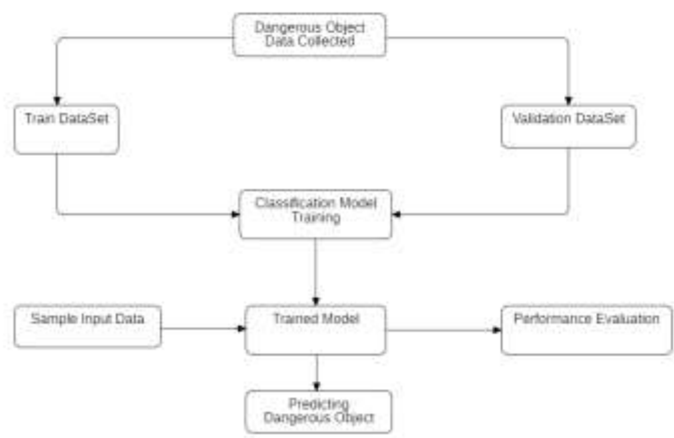
The flattened array of image pixels is provided as input to a fully connected feed forward neural network, and this layer is known as dense layer. The proposed work is implemented with 250 neurons in the hidden dense layer. The Relu activation function used for the training is as given in Eq. It is a non-linear activation function and makes sure that the output from each neuron results in a positive value.

Regularization One of the common problems faced in deep learning algorithms is overfitting. When the model performs very well on the training set but underperforms on the testing set, then such situation is known as overfitting. There are several regularization techniques [20] available that can perform well into different situations. One of the popularly used regularization technique in neural networks is dropout.

Training the Data Once the model has been built as discussed in the previous section, the model must be trained to learn the weights. To train a deep neural network, one must use an optimization algorithm. The proposed algorithm uses adaptive learning rate optimization algorithm viz. Adam [22]. It is an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. An optimization technique generally requires a loss function to map an event or values of variables onto a real number representing the cost associated with the event. The loss function viz.

Architectural Design:

Data Flow Diagram:



Results:

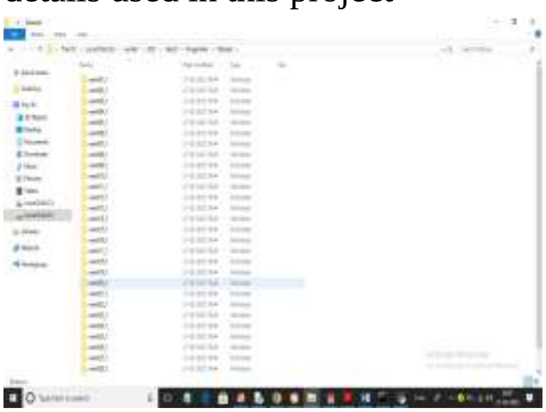
In this project we are employing Convolution Neural Network (CNN) to identify person based on finger vein. CNN will extract features from images automatically and then used this features for person identification and does not require any hand crafted features like finger minutiae or palm area HAAR cascaded files which contains finger and palm information and this files designed by humans and may contains error which result into inaccurate identification.

All existing biometric algorithms are dependent on humans hand crafted features whose prediction accuracy is not up to the mark. In propose work we are employing machine learning SVM algorithm and deep learning CNN algorithm and then evaluating both performance in terms of accuracy and confusion matrix.

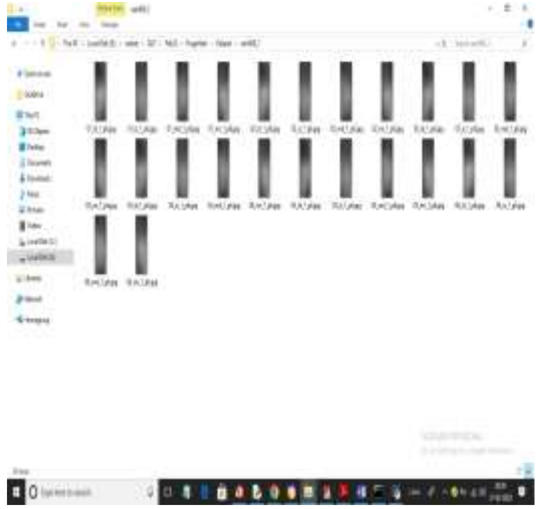
To train both algorithms we are using 30 different finger veins images dataset downloaded from KAGGLE website and below is the dataset URL. All this images are captured using Thermal cameras.

https://www.kaggle.com/datasets/ryeltsin/bdfvusm

In below screen we are showing dataset details used in this project



In above dataset screen we have 30 folders from 1 to 30 for persons finger vein from 1 to 30 and just go inside any folder to view finger vein images



In above screen we can see images of finger vein and by using above images we will trained both SVM and CNN algorithms

To implement this project we have designed following modules

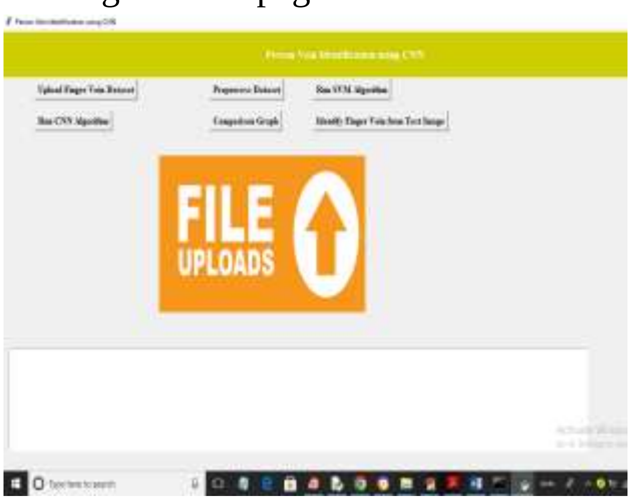
1) Upload Finger Vein Dataset: using this module we will upload dataset to application and then find and plot different person fingers found in dataset
2) Preprocess Dataset: using this module we will read image and then resize all images to equal size and then shuffle and normalize images and then split dataset into train and test where application using 80% images for training and 20% for testing
3) Run SVM Algorithm: 80% processed trained images will be input to SVM algorithm to train

a model and then 20% test images will be applied on trained model to calculate prediction accuracy

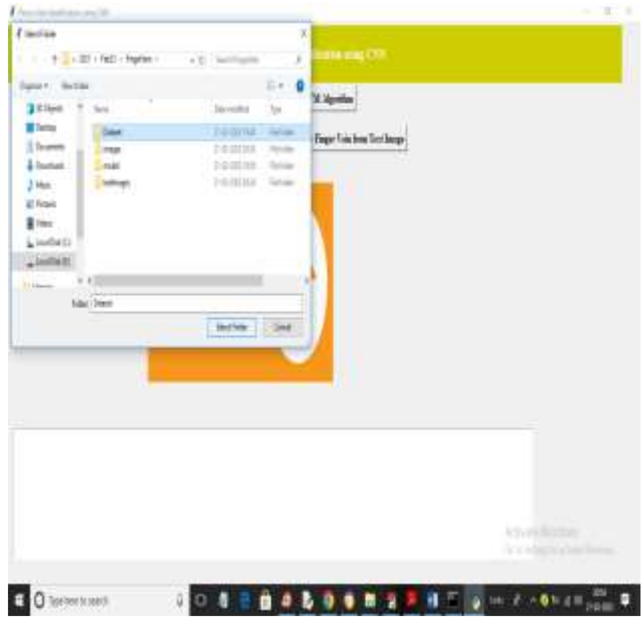
4) Run CNN Algorithm: 80% processed trained images will be input to CNN algorithm to train a model and then 20% test images will be applied on trained model to calculate prediction accuracy
5) Comparison Graph: using this module we plot comparison graph between both algorithms
6) Identify Finger Vein from Test Image: using this module we will upload test finger vein image and then CNN will analyse vein image and then identify person from that image

SCREEN SHOTS

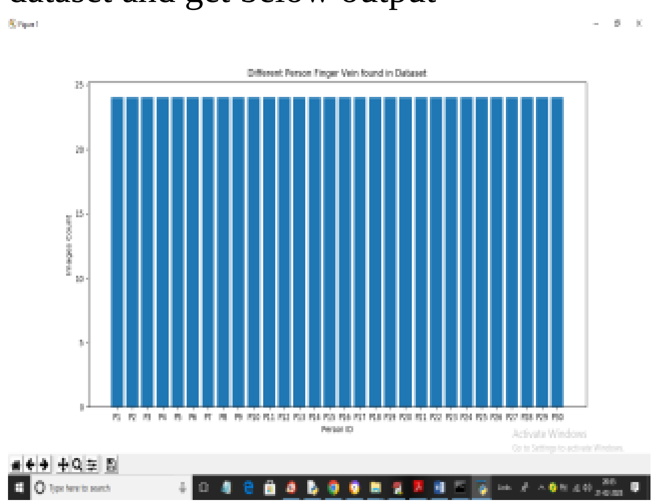
To run project double click on 'run.bat' file to get below page



In above screen click on 'Upload Finger Vein Dataset' button to upload dataset and get below output



In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and get below output



In above screen dataset loaded and in above graph x-axis represents person ID and y-axis represents number of finger images found for that person and now close above graph and then click

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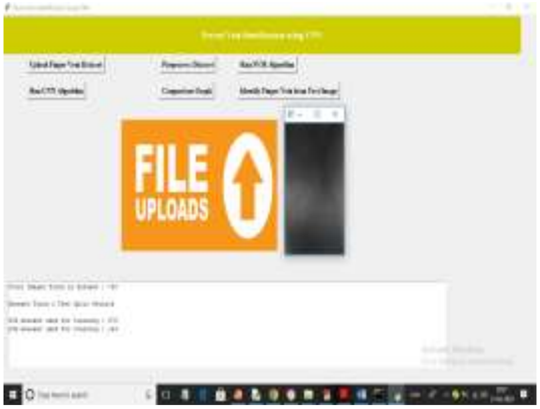
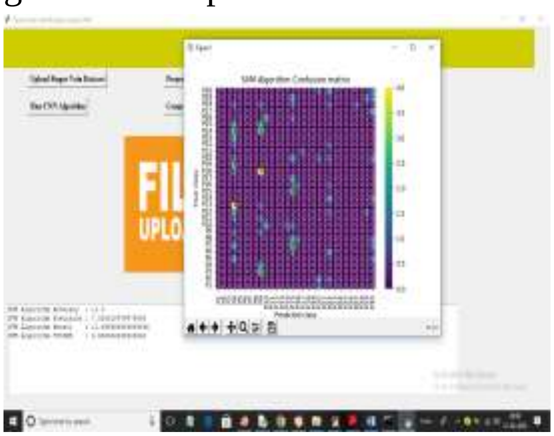
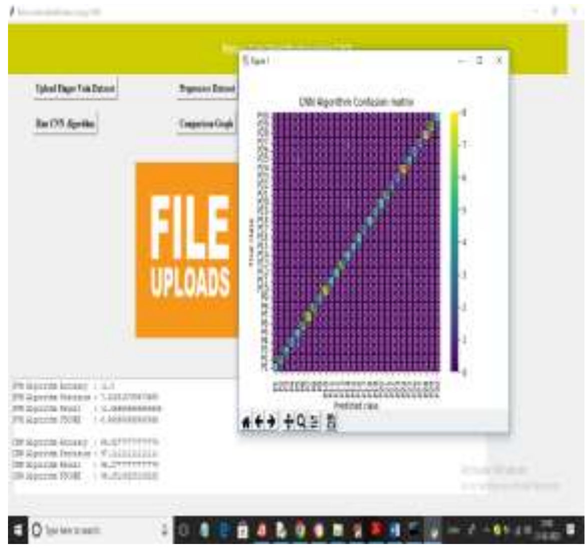
on 'Preprocess Dataset' button to process image and get below output



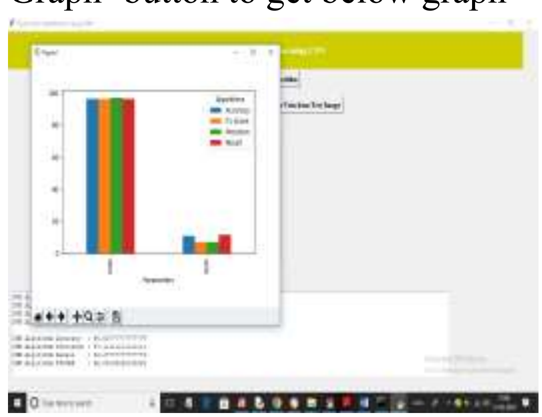
In above screen in text area we can see total processed images and can see 80% images size using for training and 20% for testing and then showing one processed image and now close above image and then click on 'Run SVM Algorithm' button to train SVM and get below output



In above screen with SVM we got 11% accuracy and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and only the count in diagnol are the correct prediction count but in above graph diagnol we are seeing very few count and remaining are 0 so SVM is not accurate and now close above graph and then click on "Run CNN Algorithm' button to train CNN and get below output



In above screen with CNN we got 98% accuracy and in confusion matrix graph in diagnol we can see all person images are correctly predicted and remaining blue colour boxes as in-corrected prediction contains 0 only. All blue colour boxes represents incorrect prediction count. Now close above graph and then click on 'Comparison Graph' button to get below graph



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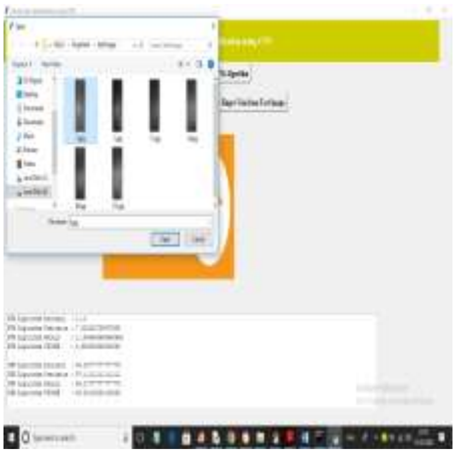
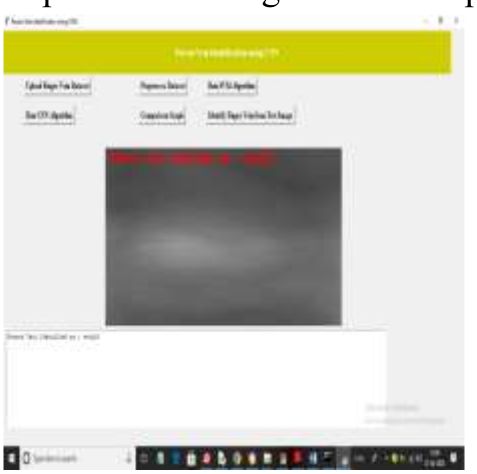
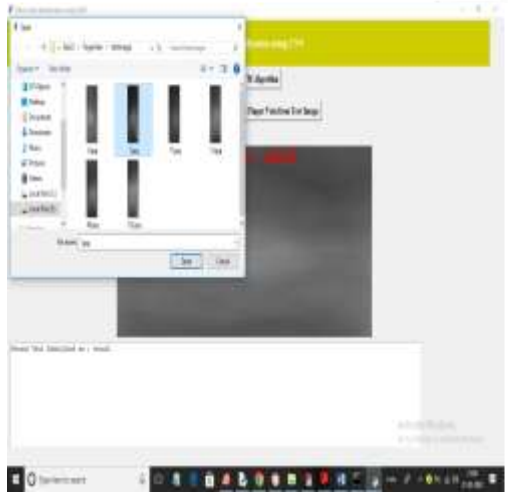
In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in both algorithms we can see CNN got high performance. Now close above graph and then click on 'Identify Finger Vein from Test Image' button to upload test finger vein image and then identify person



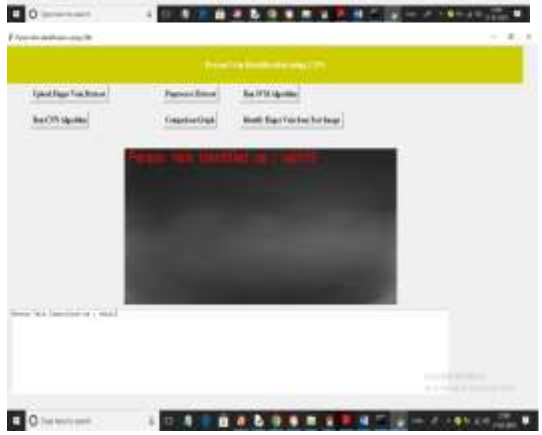
In above screen selecting and uploading '0.jpg' and then click on 'Open' button to get below output



In above screen finger vein identified for person ID 26 and similarly you can upload and test other images



In above screen uploading another image and below is the output



Conclusion:

In this paper, we have presented a novel approach to authenticate an individual based on his/her finger-vein images. The deep learning technique of convolutional neural networks is applied along with transfer learning.

The usage of transfer learning with ResNet–50 helped to achieve higher accuracy, as the learning is backed by the pre-trained model with millions of images from ImageNet database. We have used just one hidden layer with 250 neurons, and to have lower complexity, the dropout regularization is used. Appropriate optimization functions and loss functions are used to handle overfitting. As the algorithm resulted in 99.06% of accuracy in person authentication, we can conclude that the CNN model designed is found to be reasonably good.

Future Work

The future work includes reducing the false positives and negatives even more as there is still a need for improvement. We might also try to increase the number of classes or objects in the future but the priority is to further improve precision and recall.

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