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Human Identification from Palm/Dorsal Veins Using Auto encoders

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Abstract - *While it might not be prehistoric, biometrics have been around for a long time. But as technological advancement has taken place in the last century, biometrics have also been rapidly developed. Biometrics have gone from rough methods of classification to being authenticators of identity having a wide range of uses. Among these biometrics, palm vein authentication has taken a significant attention because of its uniqueness, stability, non-intrusiveness and also for it being contactless biometric. In this paper, we are proposing a palm vein authentication system using deep learning models of auto encoders. Firstly, the palm image is captured while using Infrared LEDs to get proper vein image. The region of interest (ROI) is extracted from image of palm. After extracting ROI, image is then processed by various techniques like gray scaling, histogram equalization, denoising, thresholding etc. The extracted threshold image is then passed to auto encoder model. The model then classifies the image to identify the person whose palm image it is.*

Key Words: *Authentication, Recognition, Palm vein, Biometrics, Autoencoders.*

1.INTRODUCTION

In recent years, the demand for biometrics has increased. The recent pandemic of Covid19 has given rise to increase in demand and research into contactless biometrics. This has led to evolution of many biometric applications like access control systems, attendance systems etc.

Palm vein authentication technology is a type of biometric authentication done using characteristics of palm and dorsal veins.

While comparing to other biometrics, palm vein authentication is far more secure. This is due to it having the best False Acceptance Rate(FAR) and False Rejection Rate(FRR).

Table 1 shows the comparison between various biometric authentication systems based on their FAR and FRR.

Authentication Method	FAR(%)	FRR(%)
Face Recognition	~1.3	~2.6
Voice Pattern	~0.01	~0.3
Fingerprint	~0.001	~0.1
Finger Vein	~0.0001	~0.01
Iris/Retina	~0.0001	~0.01
Palm/Dorsal Vein	**~0.00001**	**~0.01**

Table 1: Comparison between various biometric authentication systems based on their FAR and FRR

Compared to conventional biometric authentication systems like fingerprint, iris, face, palm print authentication, the characteristics palm vein pattern has several advantages. First advantage is complexity of vein makes it so that it forms unique pattern. The vein pattern between identical twins is even different. Second advantage is that vein pattern remains unchanged throughout a person's lifetime. Third advantage is that it is difficult to copy since vein pattern is an internal biometric. This means that it is present inside of palm and needs to be captured in a special camera. The biggest advantage is that vein pattern cannot be forged after death since it disappears when person dies as it relies on continuous blood flow in palm. Due to these reasons, palm vein authentication offers a great research potential and wide application prospects.

There are four stages in a typical palm vein identification system: capturing an image of the vein, pre-processing, particularly in ROI location, feature extraction, and matching (Figure 1). The collection of palm vein images is carried out using the method of palm vein image capture. To extract features from the palm vein picture, pre-processing splits a section of the image. The pre-processed palm veins are used for feature extraction, which extracts useful properties from them. Using a matcher, two palm vein characteristics are compared, and a database is used to record the results.

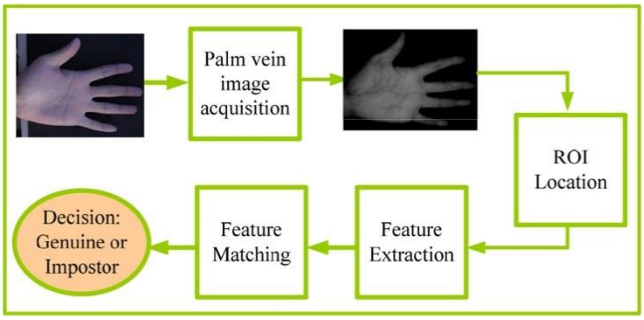

Figure 1: Palm Vein Authentication System Process

After summarizing the basic introduction about palm vein authentication in this section 1, Further section 2 elaborates the hardware setup used in this research, section 3 explains about data collection and dataset used in this research, the image processing done is explained in section 4. Section 5 elaborates on use of deep learning model of auto encoders for image classification. Lastly section 6 summarizes the conclusions and results obtained.

2. HARDWARE DESIGN AND DATA COLLECTION

The hardware architecture used in this project is explained in this section. Since palm and dorsal veins are internal biometrics, they can't have been seen using normal camera. The palm and dorsal veins can be easily seen under infrared light with NoIR camera.
Since infrared light gets absorbed by deoxygenated haemoglobin flowing towards the lungs through the veins. The NoIR camera captures the image in which the veins are seen in black faint lines and background is white.

2.1 Hardware Design

In this project we have made a matrix of infrared LEDs for appropriate hand geometry. Figure 2.a shows the hardware architecture of project and Figure 2.b shows the infrared LED matrix used in this project.

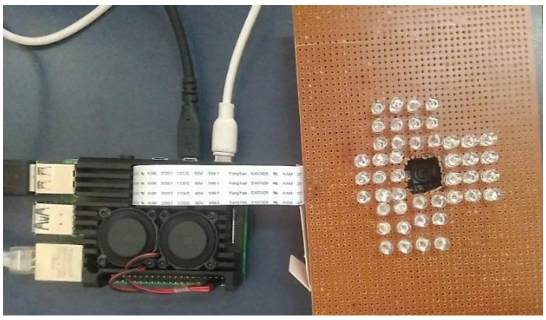

Figure 2.a: Hardware Architecture of our Palm Vein Authentication System

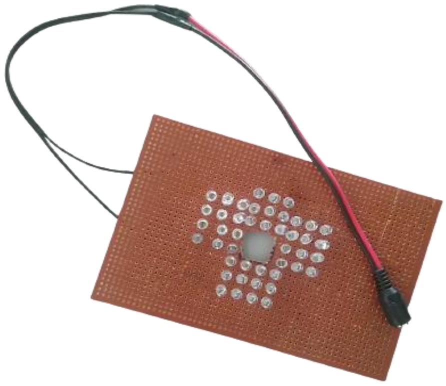

Figure 2.b: Matrix of Infrared LEDs

2.2 Dataset Collection

In this project we prepared our own dataset using the hardware setup mentioned in section 2.1. The dataset of 600 images was made. We took 20 images (5 of palm and 5 of dorsal of both hands) each of 30 people as shown in Figure 4. To obtain more accuracy, Data Augmentation technique was used. The final dataset of 6000 images was thus prepared. Figure 3 shows GUI used for Image Acquisition. Figure 4 shows the dataset of 30 people.

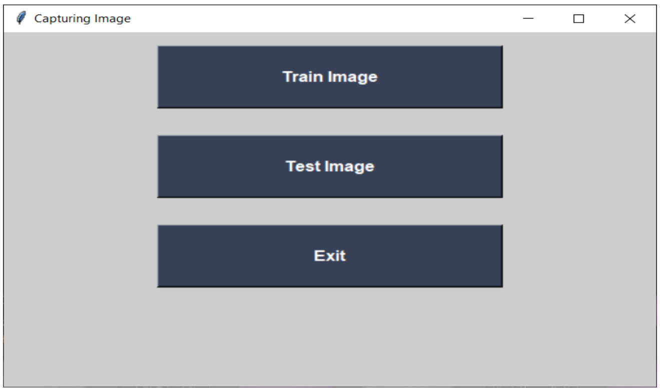

Figure 3: GUI for Image Acquisition

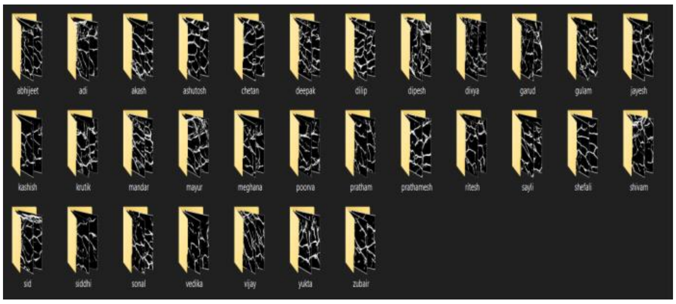

Figure 4: Dataset of 30 people.

3. IMAGE PROCESSING

To extract the vein pattern perfectly, we need to do some image processing on image that we capture. In this section, the image processing tasks used in this project to extract vein pattern are explained. Figure 5 shows the GUI used for Image Processing.

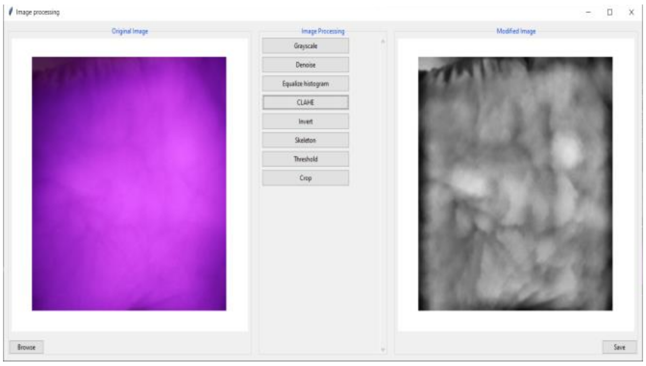

Figure 5: GUI for Image Processing

3.1 ROI Extraction

After image is captured, we first extract region of interest (ROI) from it. The ROI for palm veins is whole palm excluding the fingers, while we are taking the same for dorsal. Figure 6 shows the ROI Extraction.

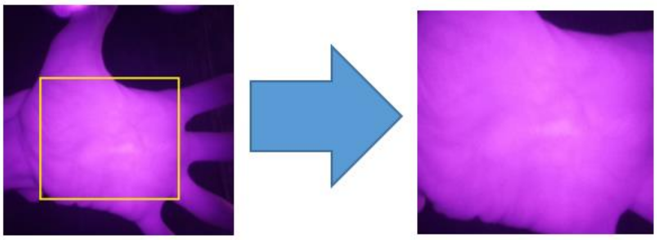

Figure 6: ROI Extraction

3.2 Converting ROI to Grayscale

The ROI image that we obtain above, is then converted to grayscale. The main reason we are gray scaling the image is that it makes extracting veins easier and also reduces computational requirements. Figure 7 shows the Grayscale Image.

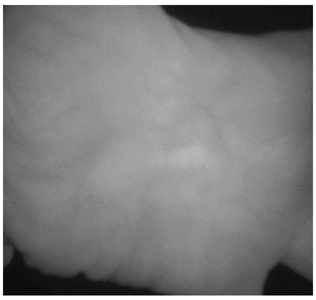

Figure 7: Grayscale Image

3.3 Denoising Grayscale Image

We then remove noise from this gray scaled image. Denoising is done because there may be some distortions in image which makes it difficult to extract the vein pattern. Figure 8 shows the Denoised Image.

Figure 8: Denoised Image

3.4 Histogram Equalization

After denoising, we are applying Contrast Limited Adaptive Histogram Equalization (CLAHE), a histogram equalization technique to make veins appear more pronounced. CLAHE is a variant of Adaptive histogram equalization (AHE) which takes care of over-amplification of the contrast. CLAHE operates on small regions in the image, called tiles, rather than the entire image. The neighbouring tiles are then combined using bilinear interpolation to remove the artificial boundaries. Figure 9 shows the Contrast Limited Adaptive Histogram Equalized Image.

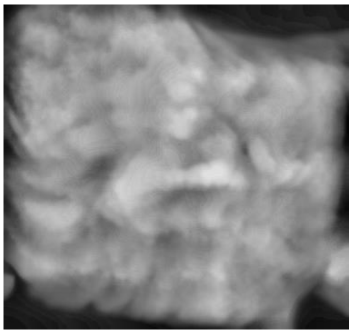

Figure 9: Contrast Limited Adaptive Histogram Equalized Image

3.5 Inverting the Image

We then invert the CLAHE image to get a black and white image with vein appearing white and rest of background as black. Colour inversion takes the original colours in an image, and then applies the colours that are the exact opposite of those colours. Figure 10 shows the Inverted Image.

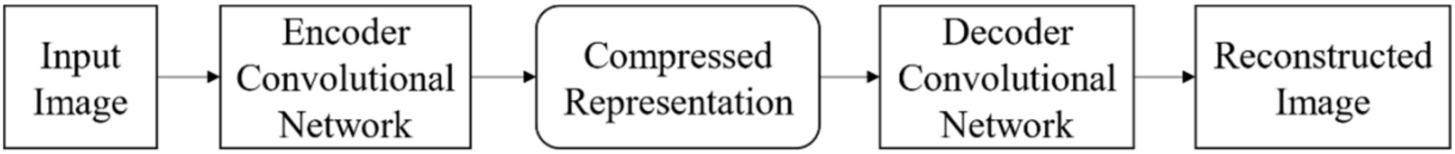

Figure 13: General Pipeline of CAE

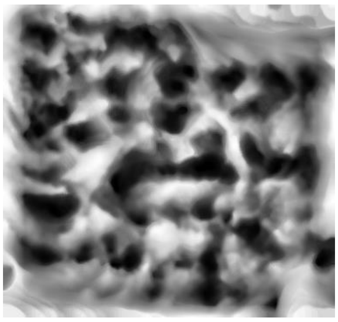

Figure 10: Inverted Image

3.6 Skeletonizing Inverted Image

Since inverted image is bit blur, we skeletonize it using repeated erosion and dilation. Skeletonization reduces the foreground regions in our binary image to a skeleton remnant which preserves main content of original image while discarding most of unneeded original foreground pixels. Figure 11 shows the Skeletonized Image.

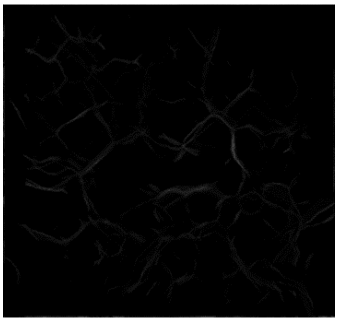

Figure 11: Skeletonized Image

3.7 Thresholding Skeletonized Image

The vein appears faint in skeletonized image, so we apply thresholding to it. This makes veins appear more pronounced.
This threshold image is what we are using for our palm vein authentication system. Figure 12 shows the Threshold Image.

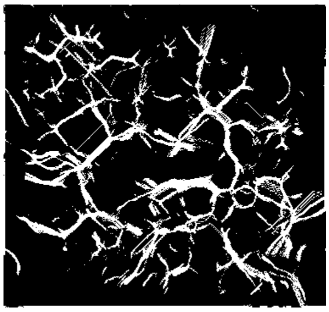

Figure 12: Threshold Image

4. AUTHENTICATION USING AUTO ENODERS

Our main task in this research project was to correctly identify a person based on person's vein pattern. To do this we need to make a multiclass classification model which would correctly classify the person based on the vein pattern.
So we tried to make a multiclass classification model first using transfer learning. We tried various pretrained models like VGG16, ResNet50, InceptionResNetV2 etc., But we found that they weren't that compatible with our dataset. The accuracy of these models was coming very low and they weren't able to properly classify our dataset. Due to this, we decided to use Convolution Auto Encoders (CAEs) for classification.

4.1 Convolution Auto Encoders

Convolution Auto Encoders (CAEs) are unsupervised dimensionality reduction models composed by convolution layers capable of creating compressed image representation. In simple words, CAEs are primarily utilized for reducing and compressing input dimension size, removing noise while simultaneously keeping all useful information and extracting the features.
CAEs are composed of two CNN models, the Encoder and Decoder. Figure 13 shows the general pipeline of CAE.

The Encoder is mainly used for encoding initial input image into latent representation which has lower dimension. Decoder in other case, is responsible for reconstructing the compressed latent representation creating an output image which is similar to initial one.

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4.2 Proposed Methodology

The figure represents main pipeline of our proposed convolution auto encoder- convolution neural network (CAE-CNN) model. In our approach, initially CAE is trained with our initial training dataset.
When CAE finishes training, the decoder part of CAE is discarded. The remaining encoder part is used for compressing the initial image dataset into compressed image dataset.
Finally, we have connected output of CAE to a fully connected layer of CNN made up of 128 nodes. This layer is again fully connected to our output layer which contains nodes as per our classes used for classification.
The performance of classification model is measured using accuracy.

4.2 Architecture of our Proposed Model

Our Model is made up of two main parts Encoder and Decoder.

Encoder has 4 Convolution blocks; each block has a convolution layer followed by a batch normalization layer. Max-pooling layer is used after the first and second convolution blocks.
The first convolution block has 32 filters of size 3 x 3, followed by a down sampling or max-pooling layer. The second block has 64 filters of size 3 x 3, followed by another down sampling layer. The third block of encoder has 128 filters of size 3 x 3. The fourth block of encoder has 256 filters of size 3 x 3.

Decoder has 3 Convolution blocks; each block has a convolution layer followed by a batch normalization layer. Up sampling layer is used after the second and third convolution blocks.
The first block has 128 filters of size 3 x 3. The second block has 64 filters of size 3 x 3 followed by another up sampling layer. The third block has 32 filters of size 3 x 3 followed by another up sampling layer. The final layer of decoder has 1 filter of size 3 x 3 which reconstructs back the input having a single channel.

The max-pooling layer down samples the input by two times each time it is used, while the up sampling layer up samples the input by two times each time it is used.

After training this model, we use the weights of CAE to train a model with only the encoder part of model which is connected with fully connected layers for classification.
Figure 14 shows the architecture of our proposed model.

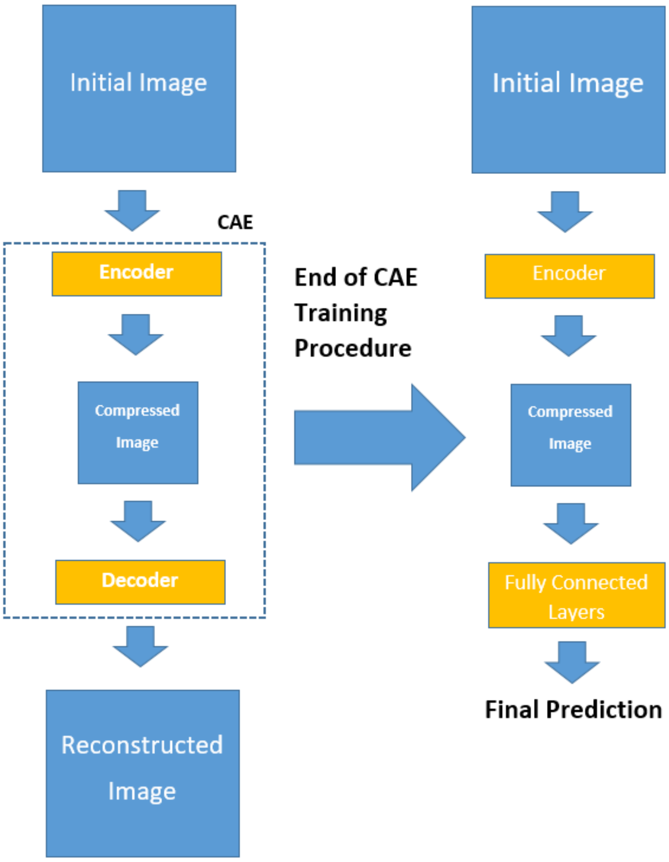

Figure 14: Architecture of our Proposed Model

5. EXPERIMENTAL RESULTS

Using the model proposed above, we obtained very high accuracy with very little loss. Figure 15 shows the graph of train loss vs validation loss.

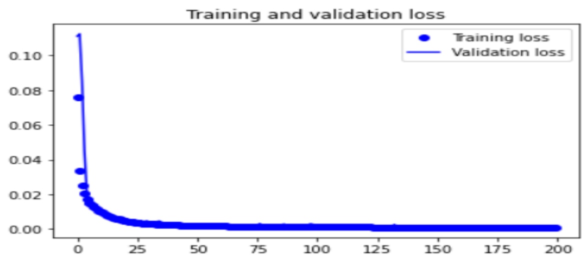

Figure 15: Graph of train loss vs validation loss

Out of 28 test images, the model correctly classified 24 images. Figure 16 shows the Correctly Classified Images.

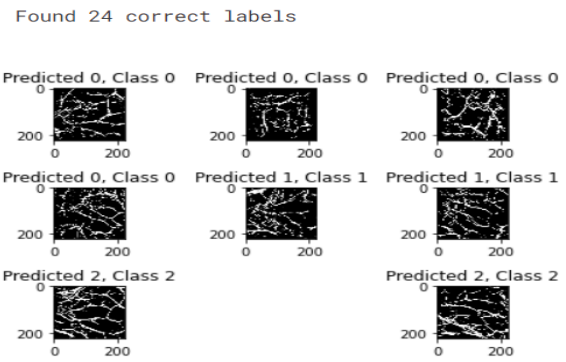

Figure 16: Correctly Classified Images

To check if the model was working perfectly, we tested it using another test image. As we can see in figure a, it was able to perfectly predict the name of person whose image it was. Figure 17 shows the GUI showing Correct Classification of Test Image.

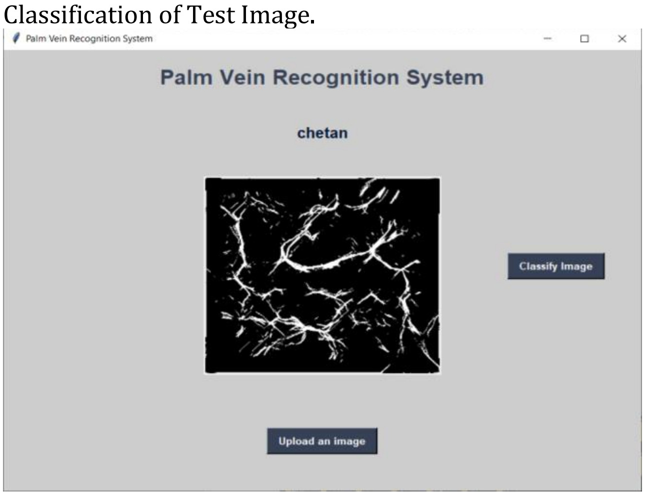

Figure 17: GUI showing Correct Classification of Test Image.

Using this we got an overall accuracy of 86 %. Figure 18 shows accuracy for seven individual Classes and overall accuracy of model.

	precision	recall	f1-score	support
Class 0	1.00	1.00	1.00	4
Class 1	1.00	0.50	0.67	4
Class 2	1.00	0.75	0.86	4
Class 3	1.00	1.00	1.00	4
Class 4	0.60	0.75	0.67	4
Class 5	1.00	1.00	1.00	4
Class 6	0.67	1.00	0.80	4
accuracy			0.86	28
macro avg	0.90	0.86	0.86	28
weighted avg	0.90	0.86	0.86	28

Figure 18: Accuracy for seven individual Classes and Overall accuracy of model.

6. CONCLUSIONS

In this paper, we proposed and suggested use of convolution auto encoder- convolution neural network (CAE-CNN) model for palm vein authentication. This model can be used to extract features from vein pattern and then correctly classify it to know the person whose vein pattern it is.

Palm Vein Technology is highly secure because it uses information contained within the body and is also highly accurate because the pattern of veins in the palm is complex and unique to each individual. Moreover, its contactless feature gives it a hygienic advantage over other biometric authentication technologies. This technology can be adopted to various fields to make better and accurate access control systems, information systems, etc.

7. FUTURE WORK

In future we aim to investigate better feature extraction techniques and combine them with our proposed model. In addition, we aim to make our proposed model more accurate and efficient. For further improvement of the system, our future work will focus on extracting the more features from the palm vein for recognition purpose like delta points, ridges, etc.

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