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CNN based Feature Extraction for Personal Authentication System using Finger Vein

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Abstract: Today's interconnected world, the online environment is crowded with data from billions of sensors, smartphones, smart watches, and other Internet of Things devices, cloud-based services, which leads to hacking threats for everyone. Securing our confidential information with proper authentication is a challenge. In this paper we propose a low cost reliable biometric system based on finger vein patterns. However, finger vein images are easily affected by uneven illumination, humidity, and finger pressure and collection posture, so quality of images gets reduced, resulting in lower performance of authentication method. To address this problem, we worked on the finger vein ROI identification method and image enhancement method by removing the noise using linear and non-linear filters. We have developed an effective CNN model in order to extract features for feature matching with enrolled images. The experiment is performed on MATLAB R2021b using the SDUMLA-HMT database. Analysis of accuracy scores and execution time, exhibit the outstanding performance of Resnet101 with the 97.64% accuracy.

Index Terms - Accuracy, CNN, Feature extraction, Finger vein, ROI, PSNR.

I. INTRODUCTION

In today's highly computerized and interconnected world, we need to exchange a lot of our private information and secrets in unsecured cyberspace. Intruders are always active and pose a threat to everyone. So the security of our confidential data has become increasingly more significant. In applications like login authentication, personal computer access, phone security, attendance system, door security, confidential video conferencing, medical diagnosis images, industrial system, military system, borderland security, online transactions, passwords, and digital signatures legal etc. are needed to control access to our confidential information and provide the means to verify the integrity of persons. In many cases, such information leakage seriously invades personal privacy.

With the help of biometric technology and devices, touch and get verified, and getting access to the system is very easy and convenient. There is no need to rush to carry your ID cards or identity related documents. In most parts of the world, many countries are working on establishing a biometric database of their citizens which is universally acceptable. Most manufacturers integrate biometric ability on mobile and computing devices for personal authentication. Since biometric is making its way to more and more applications. It is a good time to get familiarized with Biometric authentication.

Biometric is the science of identifying a person using their physiological or behavioral characteristics. Figure1 displays classification of biometrics based on physiological characteristics like face, iris, hand, finger print, finger vein and behavioral characteristics like voice, signature, keystroke (put pressure while using keyboard) ,gait (a way person walk) and mouse.

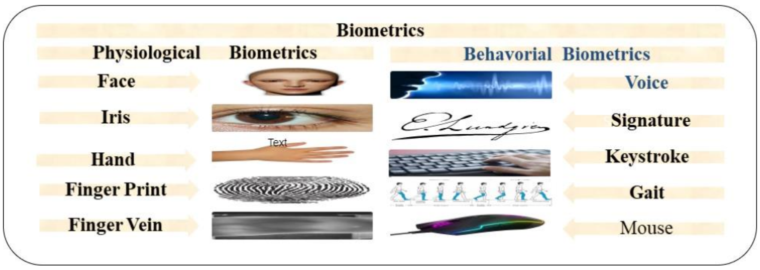

Figure1. Classification of Biometrics

In this paper, we propose an effective, reliable and low cost, user friendly biometric system based on finger vein patterns. It has gained popularity as it offers a reliable, robust and high security for personal identification. Finger vein systems has become a pioneer over other traditional identification methods such as password, keys, secret codes, paraphrase, PIN (Personal Identification Number),OTP (One Time Password), and smart cards have struggled to meet convenience, anti-spoofing and high security mechanisms. It removes all hassle associated with knowledge based ID, password and other token based or possession based authentication methods, making authentications or verification truly convenient experience.

The rest of the paper is organized as follows: Section 2 presents a brief survey of existing research work in the area of user identification and authentication using finger vein pattern. Section 3 presents finger vein authentication (FVA) methodology with a block diagram of the entire system, and also explains the necessity of ROI (Region of interest), image processing and feature extraction and matching using CNN. Section 4 elaborates the experiment and result analysis of the finger vein authentication system. The key conclusions from this work is summarized in section 5.

II. Related work:

As it is a well-known fact that the online environment is crowded with data from billions of smartphones, smart watches, sensors, cloud-based services and other IOT (Internet of Things) devices, that leads to hacking threats from every direction. In this scenarios, user identification and authentication becomes difficult. Consumers are becoming more used to, comfortable and familiar with on-device biometrics. Fingerprint identification has been usually used in mobile phones like Samsung, iPhone, and Huawei or any android phone to defend economical safety and personal privacy. Now a day's biometric research has become the hottest topic. Here we are presenting a brief survey of the related work in finger vein domain. Although the study of finger vein recognition has a shorter history as compared to fingerprint and face recognition, it has gained much attention over the last decade.

Miura et al., (2004; 2007) has proposed two methods based on finger vein pattern for feature extraction are (a) repeated line tracking and (b) maximum curvature points. Since security is an important and crucial issue. Kumar and Zhou (2011) have investigated finger vein image based human identification. Wang, Li & Memik (2010). has applied finger vein patterns to safeguard secretive information stored in the consumer electronics devices like PDA (personal digital assistant, mobile phone and laptop. Wu & Ye. (2009). has examined finger vein credentials via Radon transform based statistical features and probabilistic NN classifier (neural network). However they have used too small a database to generate reliable inferences based on the strength of such features, where the noise is present in acquired vascular patterns.

Yang et al. (2014) the author's repeatedly-used Gabor filters in OC-based methods. Liu, & Song (2012) recommended a real-time implanted finger vein recognition system for authentication on cell phones. Kong & Zhang (2004, August) has offered the famous (CompCode) competitive code, in which a bank of Gabor filters was implemented to filter the palm image. Sun et al. (2005, June) has offered orthogonal line ordinal features method and then compared with the Gaussian filtered responses of two elongated, line-like image regions, which are orthogonal in orientation, and generates a one-bit feature code. Yang et al. (2013, June) recommended a cancellable bio-cryptosystem using non-invertible properties of finger vein biometric.

Zhang, Ma & Han (2006, August) has extracted the curvelet based finger vein patterns and for classification they used a back propagation algorithm of neural networks. The performance from this approach is claimed very high but the key implementation details are missing in the paper. In 2011 Wu & Liu (2011) examined principal component analysis and the neural network for finger-vein pattern identification. Lu et al. (2014; 2013; 2017) explored finger vein authentication to secure IOT. They used HCOM (histogram of competitive orientation method) and Gabor responses for feature extraction. They also investigated the finger vein identification system with two cameras to improve the performance for posture variation effect. They also provided a detailed overview of some freely available finger vein databases for the research community in the biometric domain.

Shareef, George & Fadel (2015) has investigated finger vein identification by applying HAAR Wavelet Transform method. Hong, Lee & Park (2017) experimented with VGG-Net-16 pre-trained in order to achieve finger vein-based user verification. VGG-Net-16 comprises 13 convolutional layers, 5 pooling layers and 3 fully connected layers. Qin et al. (2013) uses multi-features fusion based scale invariant feature transform (SIFT) techniques for finger-vein verification. Hoshyar et al. (2011) has used multilayer perceptron and attained a good accuracy of 93 % but this experiment was done only on 7 subjects and 14 test templates. Das et al. (2018) investigated capabilities of a CNN model containing five convolution layers and tested this architecture 95% accuracy with four publicly available databases.

III. Method and Material

From the extensive literature survey we can infer that the FVA (Finger Vein Authentication system) is proving to be one of the fastest, most accurate and reliable personal authentication systems with very less chances of forgery as it lies beneath the person's skin, has no aging effects, is contact less, has small image capturing devices, is convenient and universally accepted.

In this section, we proposed a low cast, accurate, fastest and reliable vascular pattern based biometric system. Finger vein Authentication (FVA) works in two modes: Enrollment mode and verification mode. Figure 2 represents Finger vein Authentication phases.

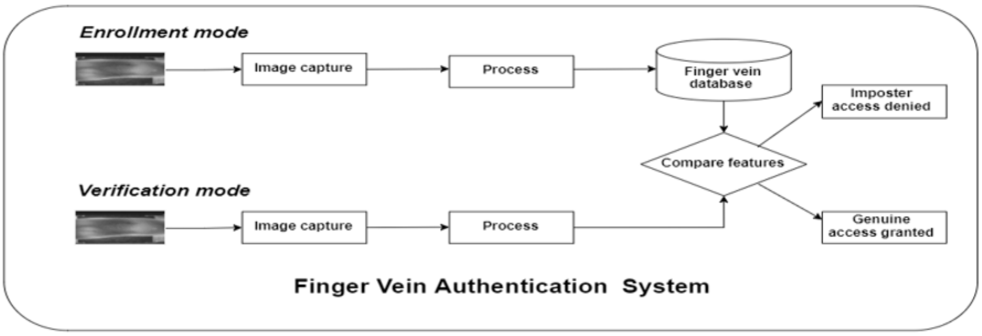

Figure 2. FVA phases.

In an enrollment mode, we initially need the finger vein image of a person captured from infrared or web camera and stored/enrolled in databases. During the authentication process, the finger vein image of a person is again captured for testing and the features (like minutiae, their location, and orientation) are extracted. These features are compared with the corresponding features in the database for associated respective ID. If there is a match then he/she recognized as genuine person and granted access to the system otherwise considered as imposter and access is rejected.

In general any finger vein identification and authentication system involves five major steps: image acquisition, ROI (region of interest), image pre-processing, feature extraction and feature matching Features will play an important crucial role in authentication of any individual. Figure 3 represented our proposed FVA Methodology.

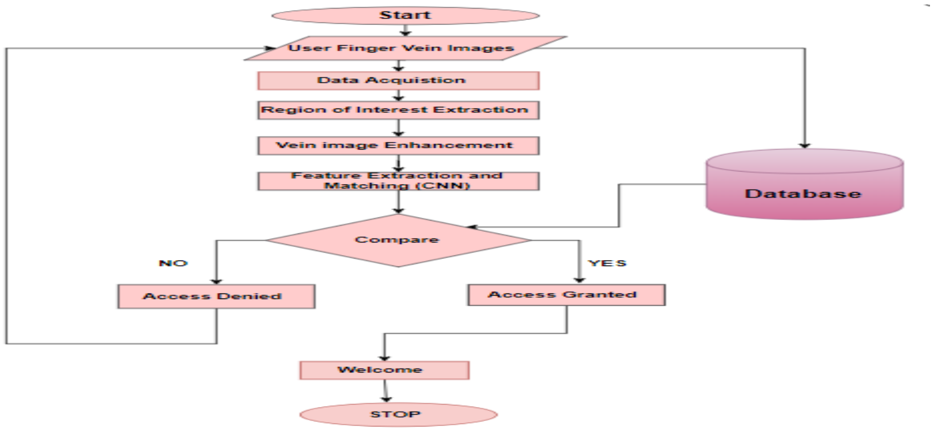

Figure 3. Flow graph of FVA Methodology

3.1 Image acquisition: The quality of the acquired finger vein image depends on the quality of the image capturing device, camera, and quality of sensor. Lightening of camera may cause an image either extremely darker or bright, distance between the finger and camera can cause optical blurring. In addition to that, the incorrect alignment or position of the finger can reduce authentication accuracy. So sometimes the guidance of the finger is also important for that reason it may happen like scattering because the human skin layer is not coherent. Some examples of finger vein scanner devices available in the market are shown in Figure 4.

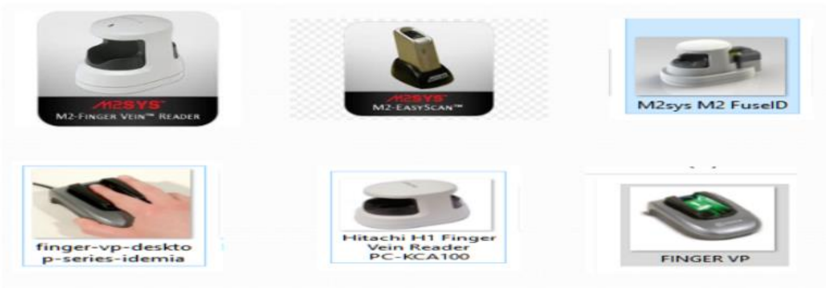

Figure 4. Finger vein Scanner

ROI (Region of Interest): One of the major problems that has to be addressed first is separation of unwanted region/background present in the image form the useful area of interest for image analysis. In order to achieve this, the images are cropped so that the information is taken mostly from the useful finger vein region. This process of finger vein identification involves ROI (Region of interest) detection using segmentation, edge detection, thresholding transformation.

3.2 Thresholding transformation: Image thresholding is generally applied to gray level or color images. Thresholding transformations are particularly useful for segmentation, in which we want to isolate a region of interest (veinous finger image) from a background (non veinous finger image). Thresholding can be classified as: (a) Global Thresholding and (b) Local Thresholding. In global thresholding, we need to choose one threshold value for the entire image, which is often based on the estimation of the background level from the intensity histogram of the image. It is well known as a point processing operation. These methods are used to automatically reduce a gray level image to a binary image. In Local threshold: the purpose of the local thresholding method is to automatically specify a threshold value T, If the pixel values below T are considered as background and the values above T are considered as foreground and vice versa. A simple method would be to choose to mean or median value all the pixels in the input image.

3.3 Image enhancement: In image preprocessing, several characteristics of the image are modified so that useful information is exploited for better vision and analyzed for better interpretability. The quality of image can be enhanced by various method such as sharpening, contrast stretching, histogram equalization, using linear and nonlinear filters, and de blurring the image by noise removal and handling the distortion caused by transformation such as rotation, scaling, orientation.

3.4 Feature extraction and feature matching: The feature extraction method can be categorized into three groups namely: (a) Vein pattern based method: The vein pattern based method have been explore in following ways: repeated line tracking, maximum curvature, mean curvature, Gabor filter, and region growth and modified line tracking method. In this method, initially the Vein patterns are segmented then the geometric shape or topological structure of the veins pattern is used for feature matching. (b)Dimensionality reduction method: Dimensionality reduction based feature method usually transforms image into low dimensional space for classification. (c) Local binary pattern method (LBP): In transformation they keep discriminating information and remove noises. Local binary methods based on local area and the extracted features are used in binary format.

Development of all these pre-processing methods and thereafter feature selection and extraction generally takes/consumes a lot of time. So the proposed system for finger vein identification involves implementation of convolutional neural network (CNN). In the pattern recognition field, finger vein detection is considered a complex part. Implementation of CNN in this area makes this complex task simple and easy. CNN is a variant of multilayer perceptron (MLP) that possesses built-in invariance.

IV. Experiment and Results Discussions

DATABASE:

For this experiment, we used 3816 finger vein images from the SDUMLA-HMT dataset. SDUMLA-HMT was collected during the summer of 2010 at Shandong University, Jinan, China. The finger vein images were enrolled by 106 volunteers including 61 males and 45 females with age between 17 and 31.The device used to capture finger vein images is designed by Joint Lab for Intelligent Computing and Intelligent Systems of Wuhan University. In the capturing process, each subject was asked to provide images of his/her index finger, middle finger and ring finger of both hands, and the collection for each of the 6 fingers is repeated for 6 times to obtain 6 finger vein images. The finger vein database is composed of 6×6×106=3,816 images. Every image is stored in "bmp" format with 320×240 pixels in size. The total size of our finger vein database is around 0.85G Bytes. (Lu, Y 2013; Yin. 2011, December).

4.1 Experiment 1: ROI

Finger veins have been emerged as an effective biometric for personal identification in recent years. However, finger vein images are easily influences by image translation, orientation, scale, scattering, finger structure, complicated background, uneven illumination, humidity, temperature, finger pressure, and collection posture, All these factors may contribute to inaccurate region of interest (ROI) definition, and so degrade the performance of finger vein identification system. To improve this problem, we worked on the finger vein ROI detection method. To identify ROI accurately, our proposed algorithm consists of three steps are: (a) Segmentation (b) Orientation correction and (c) ROI detection.

A ROI is a portion of an acquired finger vein image that we want to use as a region of interest, i.e. veinous finger image for further image preprocessing operation such as filtering. In order to get more accurate finger region, we first removed false backgrounds (i.e. unwanted finger region) from veinous finger vein region and estimate correct orientation angle for orientation correction caused by posture variation. As finger vein ROI are sensitive to finger position variation.

In our work we use a combination of thresholding as well as edge detection method for segmentation. We define ROI by creating a binary mask which is a binary image that is the same size. We set an automated threshold value using image batch processing concept for the entire dataset images. When the image pixel value is greater than the selected threshold, it will be chosen/ considered as a useful finger vein region and rest all other pixels set to 0 as background unwanted finger region were eliminated. The equation of Thresholding transformation given by equation (1) and Figure 5 depicts the creation of regions of interest.

$$\text{Thresholding Transformation: } s = \begin{cases} 1, & r > threshold \\ 0, & r \leq threshold \end{cases} \qquad (1)$$

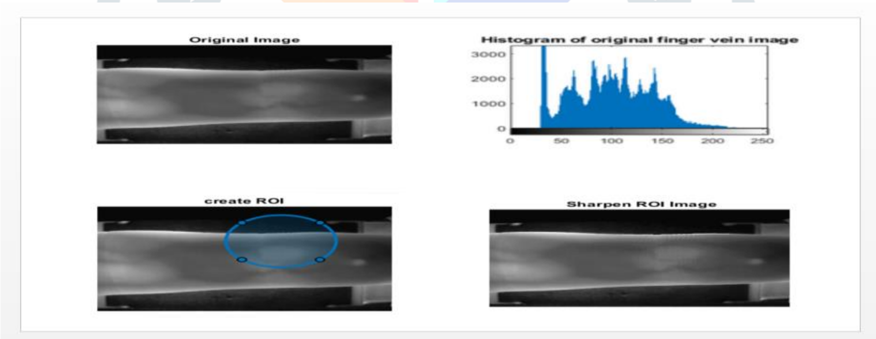

Figure 5. Creation of ROI

Our aim is to find the upper and lower finger edges, hence we applied a canny edge operator on the selected finger region. It can detect the outlines or boundaries of the finger. Then we find the boundaries closest to the horizontal center line by taking the Laplacian of the image. The width of the finger region was then obtained based on the maximum and minimum abscissa values of the finger. A Canny operator with a locally adaptive threshold was applied to get the single pixel edge of the finger. Hough transform is used to extract the binary edge image. The result of edge detection method using Sobel, Prewitt and Canny operator is shown in figure 6.

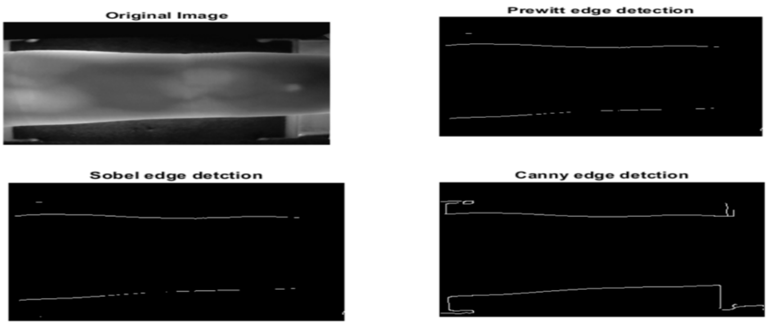

Figure 6. Edge detection of finger vein image

To remove, false background caused by uneven illumination, scattering, and improper image capturing of finger at the time of collection, from the segmented finger vein image. We used binarization of an image. To delete wrong middle edge points, we used a single linkage clustering algorithm. After that using a least-squares estimation (LSE) method, we calculated orientation angle and employed it for orientation correction.

Assuming the line function of the finger is described by y = Kx+ b , then the parameters can be directly derived according to least-squares estimation (LSE):

$$k = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^{n} (x_i - \bar{x})^2 \quad (2)$$

$$b = y - k\bar{x} \quad (3)$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (4)$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \quad (5)$$

Where x_i = 1, 2,.., n, y_i = 1,2,...,n . Hence, the corrected orientation angle between X-axis and the estimated line can be computed as follows:

$$\theta = \begin{cases} -\arctan(k), & k < 0 \\ \arctan(k), & x \geq 0 \end{cases}$$

Finally a useful ROI is detected based on searching the reference line with variation of finger width in the second knuckle of the finger. The reference line is derived from the vertical projection of the block image cropped from the segmented or orientation corrected image. Algorithm1 presents the instruction for creation of ROI from finger vein image.

Algorithm1 for ROI:

Input: User Finger vein image as input (I).Expected Output: Return ROI image of finger area (Ir).

Step1: Remove borders from user vein image (I).

Step2: Iboundary = CannyEdgeDetector(I).

Step3: ITh = AutomatedThresholding(I).

Step4: Use ITh(x,y) = ITh(x, y)(AND(NOT(Iboundary(x,y)))) at each pixel (x,y) to remove the boundary from ITh.

Step5: Extract all components from ITh by using 8-neighborhood connectivity algorithm.

Step6: Remove small size components.

Step7: Except remaining component pixels, set all other pixels as background pixels.

Step8: Ir = I.

Step9: Ir (background pixels) = 255

Step10: Return ROI image Ir.

Figure 7 demonstrated a glimpse of simulation results of creation of region of interest of finger vein dataset.

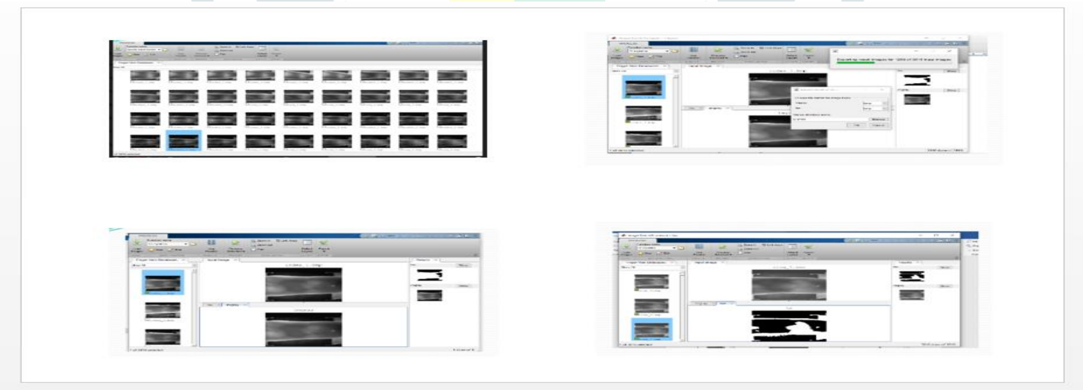

Figure 7. Simulation result of region of interest (ROI) on finger vein images

4.2 Experiment 2:

Our next objective is to enhance the quality of image for improved visualization, understanding and interpretation of image analysis. So it highlights the specific detail information hidden in an image. Some standard preprocessing techniques are (a) removal of noise (b) contrast enhancement (c) de-blurring image (d) image filtering (e) image sharpening and (f) Image smoothing.

In our work we tried to remove four different kinds of noises namely: Gaussian Noise, Salt and Pepper noise, Poisson noise and Speckle noise present in an image via implementing eight different filters such as: min, max, mean or average, median, Gaussian, Weiner, ordered and sharpen filter on our finger vein images. All simulation tasks are carried out on MATLAB R2019a using SDUMLA-HMT Database. Comparison of application of various types of filters is depicted in Table1.

Table1. Comparison of application of various filters for various types of noises on Finger Vein Database

FILTER / NOISE	METRICS	MIN	MAX	MEAN	MEDIAN	GAUSSIAN	WEINER	ORDERD	SHARPEN
GAUSSIAN	MSE	738.4683	682.9014	655.1794	607.6873	626.0082	526.8639	863.2168	555.0239
	PSNR	19.4475	19.7872	19.9672	20.294	20.165	20.9138	12.6124	20.6877
	SNR	11.652	12.4357	12.3453	12.7494	12.5711	13.3463	8.3894	14.0062
	SSIM	0.1591	0.164	0.1792	0.2756	0.1891	0.2805	0.1325	0.8263
SALT AND PEPPER	MSE	282.8637	225.1548	218.3968	180.8461	199.5797	34.9488	573.2759	36.992
	PSNR	23.615	24.606	24.7383	25.5577	25.1296	33.1415	20.5742	32.4497
	SNR	15.8196	17.2545	17.1134	17.979	17.5363	25.6067	12.4174	25.0214
	SSIM	0.6809	0.6969	0.6728	0.717	0.6922	0.9108	0.6069	0.9684
POISSON	MSE	202.8724	148.3953	144.2585	98.6689	127.1165	88.6996	839.4734	121.2173
	PSNR	25.0586	26.4166	26.5394	28.189	27.0888	28.6516	18.8907	27.2952
	SNR	17.2631	19.0651	18.9011	20.6081	19.482	21.0798	13.0647	19.9294
	SSIM	0.4963	0.5083	0.494	0.5622	0.5091	0.5415	0.428	0.8403
SPECKLE	MSE	221.2333	165.525	160.1397	117.8857	143.2796	93.6156	594.1187	133.3584
	PSNR	24.6823	25.9422	26.0858	27.4162	26.569	28.4173	18.9139	26.8806
	SNR	16.8868	18.5906	18.4463	19.8328	18.961	20.8471	13.0538	19.526
	SSIM	0.5093	0.5207	0.5086	0.5811	0.5227	0.5702	0.458	0.846

The graphical presentation of table1 is demonstrated in figure 8 and 9. For the evolution of performance measurement, we use the SSIM (Structural similarity index measure), MSE (Mean Square Error), SNR (signal to Noise ratio) and PSNR (Peak Signal to Noise ratio) metrics. The MSE and PSNR can be calculated according to formula as follows:

$$MSE = \frac{1}{MN}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - k(i,j)]^2 \tag{6}$$

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{7}$$

The higher the value of PSNR and lower MSE value, represents better quality of image. We can clearly conclude that the Wiener filter outperformed over its peer group of all the filters.

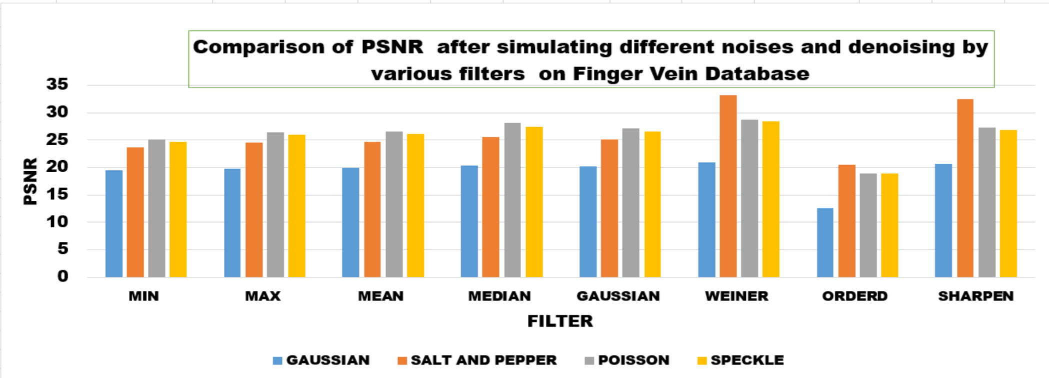

Figure 8. Comparison of PSNR on Finger Vein Database

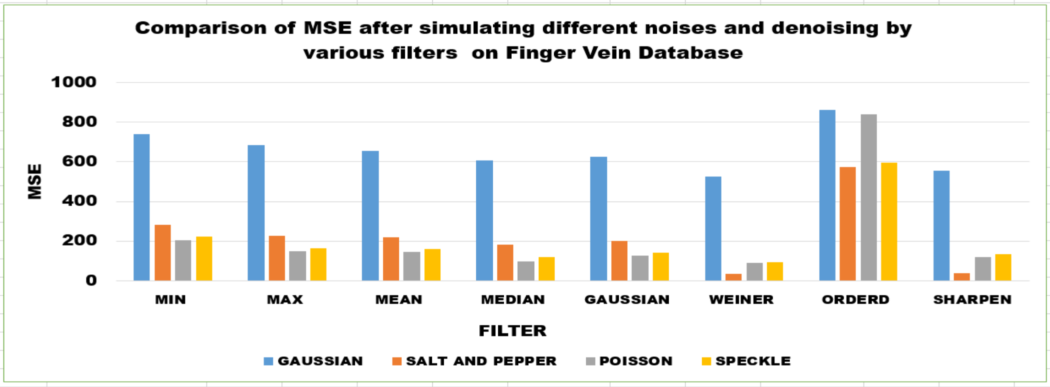

Figure 9. Comparison of MSE on Finger Vein Database

4.3 Experiment 3:

A finger vein authentication CNN model consists of an input layer, output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, normalization layers (ReLU), pooling layers and fully connected layers. Examples of a finger vein authentication CNN depicted in Figure 10.

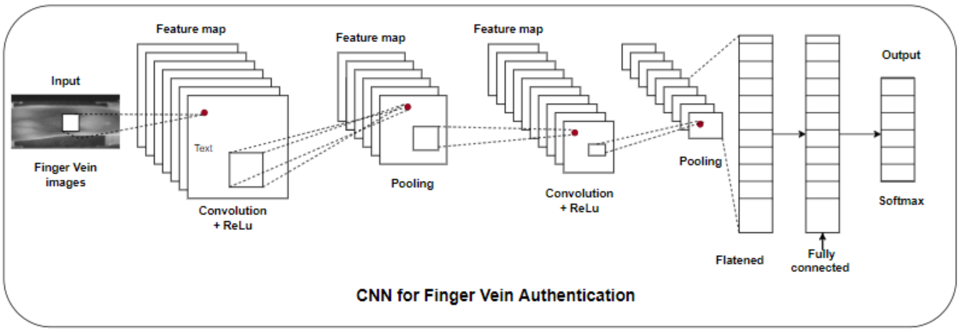

Figure 10. CNN for Finger Vein Authentication.

The overall objective of this set of experiments is to develop the CNN (Convolutional Neural Network) architecture for user authentication tasks. We implemented a transfer learning approach. Design an effective CNN model in order to extract features for feature matching with enrolled images for the finger vein authentication system. CNN is an influential machine learning technique from the deep learning province. It is a well-known fact that a collection of large divergent images is required to train CNN models. The larger the collection, the richer the features that CNN learns. These features often outperform as compared to HOG (Histogram of oriented Gradients), LBP (Local Binary Pattern) and SURF (Speeded up Robust Features).

Simulation of this experiment is carried out in MATLAB R2021b.The entire process is explained as follows: (a) preparing the dataset (b) Uploading the dataset images (c) Partition the data set into training and testing dataset (c) Loading popular pre-trained CNN models for training (d) Replace the task specific feature learnable layer (e) Image augmentation (f) Training the model (g) Testing for validation.

In this experiment, we have implemented nine different CNN models such as Alex net, Google net, Shuffle net, Squeeze net, Efficient net, Resnet101, Dense net 201, Mobile net and NAS net model on SDUMLA_HMT dataset. We partitioned the dataset into two parts: 70% finger vein images for training and 30% finger vein images for testing where the maximum number of the epoch equal to 6 and the mini-batch size equal to 267, maximum iteration=1602, learning rate is 0.0003. After training, the networks can identify the person's finger vein and display the predicted label and prediction probability for the images in the dataset. Table2 and Figure11. Demonstrate the outcome of comparative analysis of FVR (Finger Vein Recognition) of nine popular CNN models with splitting of dataset in ratio (70:30) for training and testing dataset in terms of accuracy in percentage and time in minutes.

Table2. Comparative FVR CNN (70:30)

Sno.	CNN Model	Accuracy in %	Time in minutes	Layers	Training	Testing	Learning rate	Epoch
1	Alexnet	82.17	14	25	2672	1144	3.00E-04	6
2	Squeezenet	87.06	10.23	68	2672	1144	3.00E-04	6
3	Googlenet	92.22	19.54	144	2672	1144	3.00E-04	6
4	Shufflenet	92.05	26.1	172	2672	1144	3.00E-04	6
5	Efficientnet	87.59	73.23	290	2672	1144	3.00E-04	6
6	Resnet101	97.64	83.29	347	2672	1144	3.00E-04	6
7	Densenet201	97.2	236.34	768	2672	1144	3.00E-04	6
8	Mobilenet	94.14	175.52	154	2672	1144	3.00E-04	6
9	NASnet	82.87	251.37	913	2672	1144	3.00E-04	6

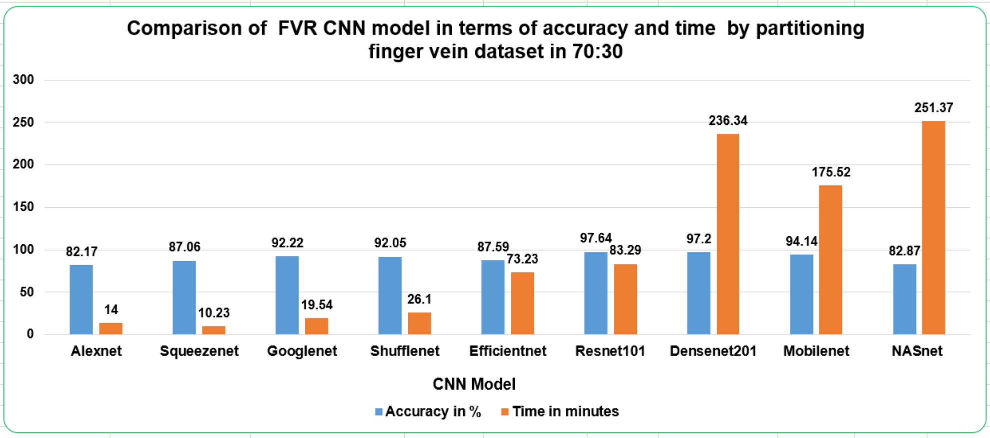

Figure 11. Comparison of FVR CNN (70:30)

Now we again repeat the above experiment by partitioning the dataset into two parts: 80% finger vein images for training (i.e. 3052 images) and 20% finger vein images for testing (i.e. 764 images) where the maximum number of the epoch equal to 6 and the mini-batch size equal to 305, maximum iteration=1830, learning rate is 0.0003. After training, the networks can identify the person's finger vein and display the predicted label and prediction probability for the images in the dataset.

Table3 and Figure12 demonstrate the outcome of comparative analysis of FVR (Finger Vein Recognition) of nine popular CNN models with splitting of dataset in ratio (80:20) for training and testing dataset in terms of accuracy in percentage and time in minutes.

Table3. Comparative FVR CNN (80:20)

Sno.	CNN Model	Accuracy in %	Time in minutes	Layers	Training	Testing	Learning rate	Epoch
1	Alexnet	84.95	15.29	25	3052	764	3.00E-04	6
2	Squeezenet	87.57	11.28	68	3052	764	3.00E-04	6
3	Googlenet	93.39	19.57	144	3052	764	3.00E-04	6
4	Shufflenet	90.31	27.43	172	3052	764	3.00E-04	6
5	Efficientnet	86.78	75.57	290	3052	764	3.00E-04	6
6	Resnet101	97.64	89.56	347	3052	764	3.00E-04	6
7	Densenet201	96.34	192.21	768	3052	764	3.00E-04	6
8	Mobilenetv2	95.29	254.48	154	3052	764	3.00E-04	6
9	NASnet	89.92	300.1	913	2672	1144	3.00E-04	6

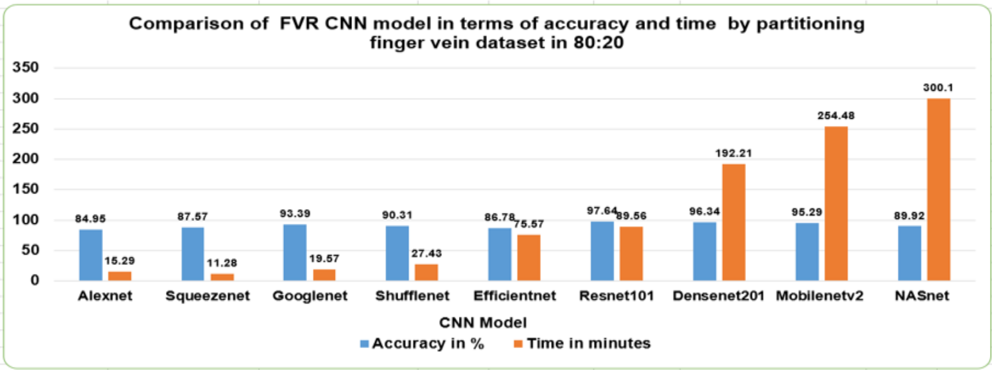

Figure 12. Comparison of FVR CNN (80:20)

V. CONCLUSIONS:

In this paper, we proposed ROI method to eliminate false background caused by uneven illumination, humidity and posture variation caused by image translation scattering, orientation, and pressure one puts while capturing the finger vein image for identification and verification of individuals. We have used the LSE method to correct its orientation. Then in the second experiment we performed image pre-processing/enhancement operation for better visualization analysis of finger vein by removing the noise which is inevitable itself while capturing by imaging devices or camera. We conclude that the Wiener filter performed excellently in its peer group of 8 different filters supported by the standard metric such as SNR, PSNR, MSE and SSIM. Finally, in the third experiment, we have used nine popular CNN models to leverage the power of CNN. It saves a huge amount of time and effort as a feature extractor and for verification of persons. However training a CNN with a large set of divergent images is not an easy task. The experiment is performed on MATLAB R2021b using the SDUMLA-HMT database. Analysis of accuracy scores and execution time required for personal verification exhibit the outstanding performance of Resnet101 with the 97.64% accuracy over other networks.

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REFERENCES

[1] Das, R., Piciucco, E., Maiorana, E., & Campisi, P. (2018). Convolutional neural network for finger-vein-based biometric identification. IEEE Transactions on Information Forensics and Security, 14(2), 360-373.

[2] Hong, H. G., Lee, M. B., & Park, K. R. (2017). Convolutional neural network-based finger-vein recognition using NIR image sensors. Sensors, 17(6), 1297.

[3] Hoshyar, A. N., Sulaiman, R., & Houshyar, A. N. (2011). Smart access control with finger vein authentication and neural network. J. Am. Sci, 7(9).

[4] Kong, A. K., & Zhang, D. (2004, August). Competitive coding scheme for palmprint verification. In Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004. (Vol. 1, pp. 520-523). IEEE.

[5] Kumar, A., & Zhou, Y. (2011). Human identification using finger images. IEEE Transactions on image processing, 21(4), 2228-2244.

[6] Liu, Z., & Song, S. (2012). An embedded real-time finger-vein recognition system for mobile devices. IEEE Transactions on consumer Electronics, 58(2), 522-527.

[7] Lu, Y., Wu, S., Fang, Z., Xiong, N., Yoon, S., & Park, D. S. (2017). Exploring finger vein based personal authentication for secure IoT. Future Generation Computer Systems, 77, 149-160.

[8] Lu, Y., Xie, S. J., Yoon, S., Wang, Z., & Park, D. S. (2013, December). An available database for the research of finger vein recognition. In 2013 6th International congress on image and signal processing (CISP) (Vol. 1, pp. 410-415). IEEE.

[9] Lu, Y., Yoon, S., & Park, D. S. (2014). Finger vein identification system using two cameras. Electronics Letters, 50(22), 1591-1593.

[10] Lu, Y., Yoon, S., Xie, S. J., Yang, J., Wang, Z., & Park, D. S. (2014, August). Finger vein recognition using histogram of competitive gabor responses. In 2014 22nd International Conference on Pattern Recognition (pp. 1758-1763). IEEE.

[11] Miura, N., Nagasaka, A., & Miyatake, T. (2004). Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification. Machine vision and applications, 15(4), 194-203.

[12] Miura, N., Nagasaka, A., & Miyatake, T. (2007). Extraction of finger-vein patterns using maximum curvature points in image profiles. IEICE TRANSACTIONS on Information and Systems, 90(8), 1185-1194.

[13] Qin, H., Qin, L., Xue, L., He, X., Yu, C., & Liang, X. (2013). Finger-vein verification based on multi-features fusion. Sensors, 13(11), 15048-15067.

[14] Rosdi, B. A., Shing, C. W., & Suandi, S. A. (2011). Finger vein recognition using local line binary pattern. Sensors, 11(12), 11357-11371.

[15] Shareef, A. Q., George, L. E., & Fadel, R. E. (2015). Finger vein recognition using haar wavelet transform. International Journal of Computer Science and Mobile Computing, 4(3), 1-7.

[16] Sidiropoulos, G. K., Kiratsa, P., Chatzipetrou, P., & Papakostas, G. A. (2021). Feature Extraction for Finger-Vein-Based Identity Recognition. Journal of Imaging, 7(5), 89.

[17] Sun, Z., Tan, T., Wang, Y., & Li, S. Z. (2005, June). Ordinal palm print representation for personal identification [representation read representation]. In 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05) (Vol. 1, pp. 279-284). IEEE.

[18] Wang, D., Li, J., & Memik, G. (2010). User identification based on finger-vein patterns for consumer electronics devices. IEEE Transactions on Consumer Electronics, 56(2), 799-804.

[19] Wu, J. D., & Liu, C. T. (2011). Finger-vein pattern identification using principal component analysis and the neural network technique. Expert Systems with Applications, 38(5), 5423-5427.

[20] Wu, J. D., & Ye, S. H. (2009). Driver identification using finger-vein patterns with Radon transform and neural network. Expert Systems with Applications, 36(3), 5793-5799.

[21] Yang, J., & Shi, Y. (2014). Towards finger-vein image restoration and enhancement for finger-vein recognition. Information Sciences, 268, 33-52.

[22] Yang, W., Hu, J., & Wang, S. (2013, June). A finger-vein based cancellable bio-cryptosystem. In International Conference on Network and System Security (pp. 784-790). Springer, Berlin, Heidelberg.

[23] Yang, W., Huang, X., Zhou, F., & Liao, Q. (2014). Comparative competitive coding for personal identification by using finger vein and finger dorsal texture fusion. Information sciences, 268, 20-32.

[24] Yin, Y., Liu, L., & Sun, X. (2011, December). SDUMLA-HMT: a multimodal biometric database. In Chinese Conference on Biometric Recognition (pp. 260-268). Springer, Berlin, Heidelberg.

[25] Zhang, Z., Ma, S., & Han, X. (2006, August). Multiscale feature extraction of finger-vein patterns based on curvelets and local interconnection structure neural network. In 18th International conference on pattern recognition (ICPR'06) (Vol. 4, pp. 145-148). IEEE.

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