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# Biometric Signal Classification Using Convolutional Neural Network

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## Abstract

In this paper, we introduce an approach to classifying the biometric signal using Convolutional Neural Network (CNN) technology, Image processing, Improved image, Extract features for images, and Image classification-using CNN. In the image-processing phase, we choose the possibility of interest in the ROI and make improvements to the images using the Histogram Equalization method. The feature extraction phase uses three techniques (CNN, SURF, and LBP) which are used in the field of image classification and identification of results with good results. Stage classification of finger vein images using CNN, showed high accuracy compared to other technics.

**Keywords:** Biometric, Finger Vein, feature Extraction, Image Classification, Convolution Neural Network.

**الملخص**

في هذه الورقة ، نقدم طريقة لتصنيف الإشارة البيومترية باستخدام تكنولوجيا الشبكة العصبية (CNN) ، ومعالجة الصور ، وتحسين الصور ، وميزات استخراج الصور ، وتصنيف الصور باستخدام CNN . في مرحلة معالجة الصور، نختار إمكانية الاهتمام من ROI ونقوم بإجراء تحسينات على الصور باستخدام طريقة Histogram Equalization . تستخدم مرحلة استخراج الميزات ثلاثة تقنيات (CNN ، SURF، وLBP) والتي تستخدم في مجال تصنيف الصور وتحديد النتائج بنتائج جيدة. أظهرت مرحلة تصنيف صور وريد الإصبع باستخدام CNN دقة عالية مقارنة بالتقنيات الأخرى.

**الكلمات المفتاحية:** القياسات الحيوية ، إصبع الوريد ، ميزة استخراج ، تصنيف الصورة ، شبكة العصبية الملتوية.

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## 1. Introduction

The Classification is a data processing task in which images are classified into several collections. Categorization of scenery allows us to efficient and quick analysis possibility. A scene is characterized as a place in which we can move. Classifying scenery (like outdoor, indoor) is not a simple mission if it consists blurry and noisy content. The scenery classification issue has two critical components representing scenery's and learning models for semantic categories using these representations. When images include stoppage, poor quality, noise or background clutter it is very harsh to recognizing an object in an image and this mission becomes even more challenging when an image contain multiple objects. To identify the features obtain in an image is the major objective of image classification. Supervised classification and unsupervised classification are the two main image classification methods. In manage classification, study database is needed and person annotation is required. In unsupervised classification, human annotation is not required and it is more computer automated (Manshor et al., 2012).

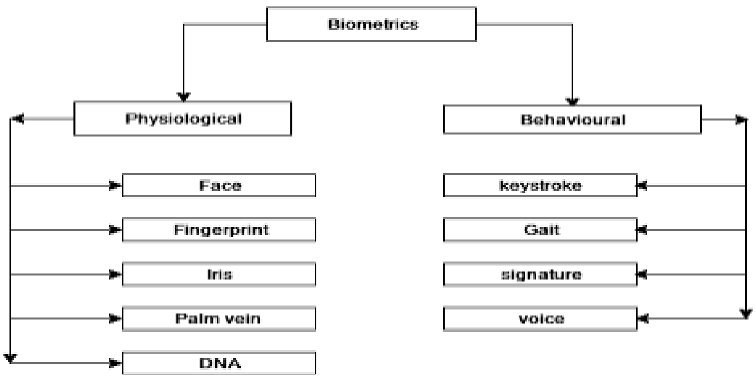


**Fig. 1 Classification of biometrics**

Classification of biometrics finger vein recognition is a personal physiological characteristics-based biometric technique, and it employs vein patterns in human finger to implement identity authentication. Nearer-infrared illumination (wavelengths between 700 and 1,000 Nanometers) is usually used to take a finger vein image (Hashimoto, 2006; Miura et al., 2004). The principle is that, near-infrared light is often absorbed intensively by the hemoglobin within the blood of vein, but transmits other tissues of finger easily, therefore the vein pattern in finger is going to be captured as shadows. As a biometric characteristic, finger vein has several-desired attribute, like universality, distinctiveness, duration and acceptability.

Additionally, compared with other biometric characteristics (for example, face, gait, fingerprint, then on), its other distinct advantages within the following two points (Miura et al., 2004): (1) Living body identification. It means only vein in living finger are often captured, and further want to perform identification. (2) Internal characteristic. It is hard to repeat or forge finger vein, and little external factor can damage finger vein, which guarantee the high security of finger vein recognition. These two advantages make finger vein an irreplaceable biometric characteristic, and attract more and more attentions from research teams. A model finger vein identification method mainly includes a picture acquisition, pre-processing, feature extraction and matching, as shown in Fig.1. Kono (2000), Japanese medical researchers suggested finger vein based identity identification, and award an effective feature extraction method (Yanagawa et al., 2007). Exemplary finger vein identification arrangement.

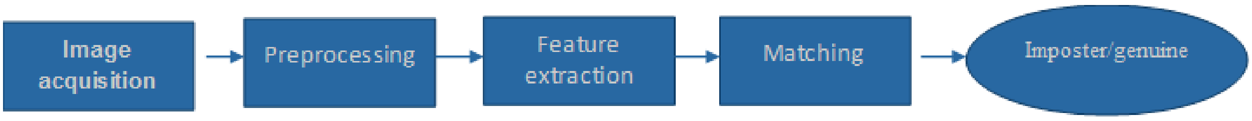


**Fig. 2 Typical finger vein identification system.**

## 2. Related work

Proposed face annotation approach using SURF detection technique and nearest neighbor search. Feature extraction is done using SURF detection technique and tags are provided to the image using these nearest neighbors. Taking the idea of label independence for image annotation. This approach takes care of the problem of annotation of labelled, unlabeled and weakly labelled images; also, it can be stretched out to different types of images than facial images. The images under different conditions are also recognized by this system like low light images, blurred images. In this, paper authors proposed framework of search based image annotation (Paul and AS, 2015) proposed age estimation system using convolutional neural network (CNN). Feature extraction and classification are important tasks in an age estimation system. CNN is employed to extract the countenance in feature extraction part. By building a multilevel convolutional neural network model, convolution activation features are gained which is predicated on abundant training data (Yan et al., 2014).

Proposed an automatic face annotation which utilizing facial; features, clothing colors and date. Face detection, feature extraction and face annotation are three noteworthy operations of this approach. In face detection, frontal faces are detected from the photo collection. In this approach, face is detected by Viola and Jones Haar-like detector. Facial features, colors of clothing and date of picture are extracted after the face detection and stored as feature vectors. To recognize the face, metric distance similarity measure is used. The task of face annotation is completed by measuring the feature similarities between the input picture and the trained pictures. Patel and Shah (2017) portrayed Local Binary Pattern (LBP) and It's altered models Multivariate Local Binary Pattern (MLBP), Centre Symmetric Local Binary Pattern (CS-LBP) and Local Binary Pattern Variance (LBPV) and evaluate the performance. K nearest neighbor classification algorithm is utilized to extract and compared the facial features. Classification is done by the G-statistics distance measure. Experimental demonstrates CS-LBP give higher recognition rate compare to LBP, MLBP and LBPV. Less computational time is devoured by the CS-LBP.

## 3. Theoretical background

### *3.1 Speeded Up Robust Features (SURF)*

Speeded up Robust Features (SURF) is a local feature detector and descriptor. The standard version of SURF is numerous times faster than SIFT. SURF gives robust results against different image transformations compared to SIFT. SURF detectors discover the interest points in a picture. To detect interest points, SURF utilizes an integer approximation of the determinant of Hessian blob detector, which may be computed with three integer operations employing a pre-counted integral image (Paul and AS, 2015). Its feature descriptor is based on the sum of the Haar wavelet response about the point of interest. These can be computed with the assist of the integral image. SURF is invariant to a scale and in-plane rotation features. Feature vectors during SURF are created by means of native patterns about key-points who are discovered using scaled up filter. Main steps performed in SURF are interest point detector and interest point characterization (Paul and AS, 2015).

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### *3.2 Local Binary Pattern (LBP)*

Local gray level frame is summed up employing local binary pattern factor. LBP is helpful because it is resistive to lighting effects and effective for texture analysis and classification from (Patel and Shah, 2017). Facial image is partitioned into numerous blocks and features are extracted over the blocks by the LBP. LBP operator considers 3×3 and different neighborhood to label the pixels of an image by thresholding.

$$LBP_{p,r} \sum_{p=0}^{p-1} s(g_i - g_c)2^i, s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & otherwise \end{cases}$$

Where gc is that the center picture element gray level. gi (i=0, 1,..7) Is that the gray level of every encompassing picture element? If gi is smaller than gig cycle, the binary results of the picture element is about to zero otherwise set to one. All the results square measure combined to urge eight-bit worth. LBPp,r represent the LBP feature of a pixel's circularly neighborhoods.

### *3.3 Neural Network*

A neural network is based on the basis such that it receives a set of input (X1, X2…Xn). This set of inputs is multiplied by a set of weights (W1, W2, and Wn). These weighted values are then summed and the output is passed through an activation (transfer) function The activation function is also indicate to as a squashing function in that it squashes (limits) the allowable range of the output signal to some finite value In mathematical terms, the neuron is fired when (X1 * W1 + X2 *W2 + ……+ Xn * Wn) >T, where T is a defined threshold value.

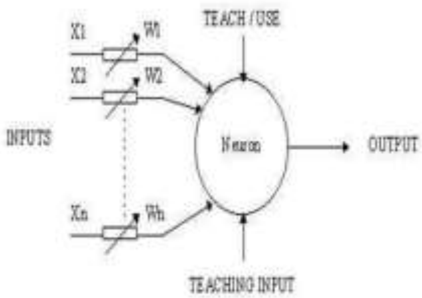


**Fig. 3 Neural Network Methodology**

### *3.4 Artificial Neural Network Based Classification (ANN)*

ANN may be a computational type inspired by the biological neural network. It can be deemed as a weighted directed graph within which nodes are neurons and edges with weights are connected among the neurons. Each artificial neuron computes a weighted sum of its input signals and generates an output, supported certain activation functions, like piecewise linear, sigmoid, Gaussian, etc. It consists of one input layer, one output layer, and counting on the appliance it is going to or might not have hidden layers. The amount of nodes at the output layer is adequate to the amount of data classes, whereas the amount of nodes at the input is adequate to the dimensionality of every pixel. Feed-forward ANN with the back propagation-learning algorithm is most commonly hired in ANN literature. In the learning stage, the network must learn the connection weights iteratively from a set of training samples. The network gives an output, corresponding to each input. The created output is compared to the desirable output. The error between these two is used to adjust the weights of the ANN. The training procedure ends when the error turns out less than a predefined threshold. Then, all the test data are fed into the classifier to perform the classification (Artificial intelligence neural networks, 2020).

#### *3.4.1 Types of Artificial Neural Networks*

There are two Artificial Neural Network topologies Feed Forward and Feedback. In Feed Forward ANN, the information stream is unidirectional. A unit sends data to another unit from which it does not get any data. There are not any feedback loops. They are utilized in pattern generation/recognition/classification. They need settled sources of input and outputs. It is Illustrated (Ujjwalkarn, 2016**)**. In Feedback ANN, feedback loops are permitted. They are used in material addressable memories.

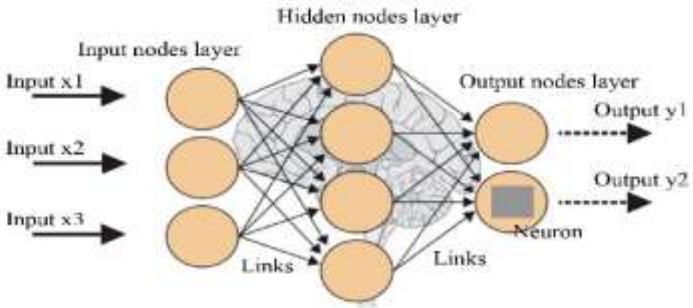


**Fig. 4 Basic structure of an artificial neural network (ANN)**

*3.5 Convolutional Neural Network (CNN)*

Convolutional neural network (CNN) is the deep learning method. Convolutional neural network (CNN) is broadly used as a part of image recognition and speech analysis. CNN is useful in study of recognition during the variability of 2D shapes. It combines local feature fields along with shared weights. It also uses the spatial sub-sampling to consider shifting level, deformation and scale invariance (Xiaopeng et al., 2018). Convolutional network contains bunches of layers which composed of the many neuron planes. Each unit within the plane is related to past layer using local neighborhood. In CNN, each layer possesses many feature maps. The output of one layer is that the input of next layer (Xiaopeng et al., 2018). The unit contains local feature detector and its activation characteristic is obtained in learning phase. The outputs from set of units combine to form a feature map. The same operation is to be applied on every a neighborhood of the image or older feature maps for all the units during a feature map to extract all features from the same image (Xiaopeng et al., 2018).

After scanning the input image with single unit with weights to make local receptive field and store the outputs of first unit in its related locations within the sequenced feature map. Convolutional feature maps take a level of invariability for translations and distortion. It includes features having decreasing order spatial resolution as complexity increases also as globally detecting from units within the successive layers.

Following subsections will provide a detailed description of unlike layers of a CNN:

1) Convolutional Layer.2) ReLU: The rectified linear unit. (ReLU) 3) Pooling layer.4) Fully Connected Layer.

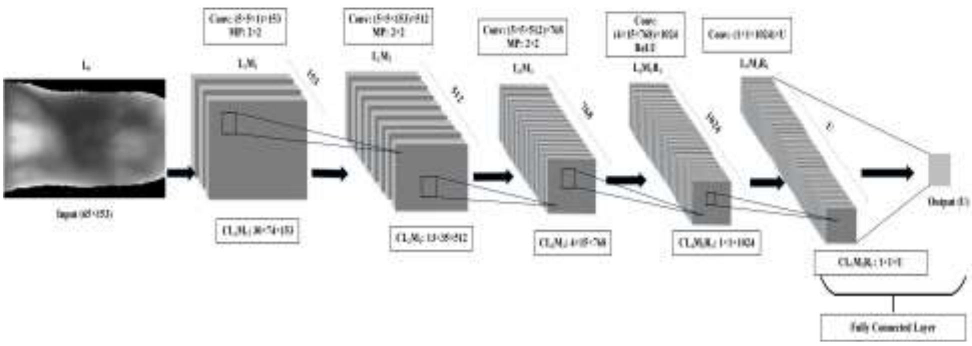

**Fig. 5 Employed CNN architecture**

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## 4. Proposed Method

### *4.1 Finger-Vein Image Pre-processing*

In general, the aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing. Herein, the aim of finger vein image pre-processing is to enhance some image features relevant for further processing task. As a result, interesting details in the image are highlighted and noise is removed from the image. Finger images include noise with rotational and translational variations. To eliminate these variations, it is subjected to pre-processing steps.

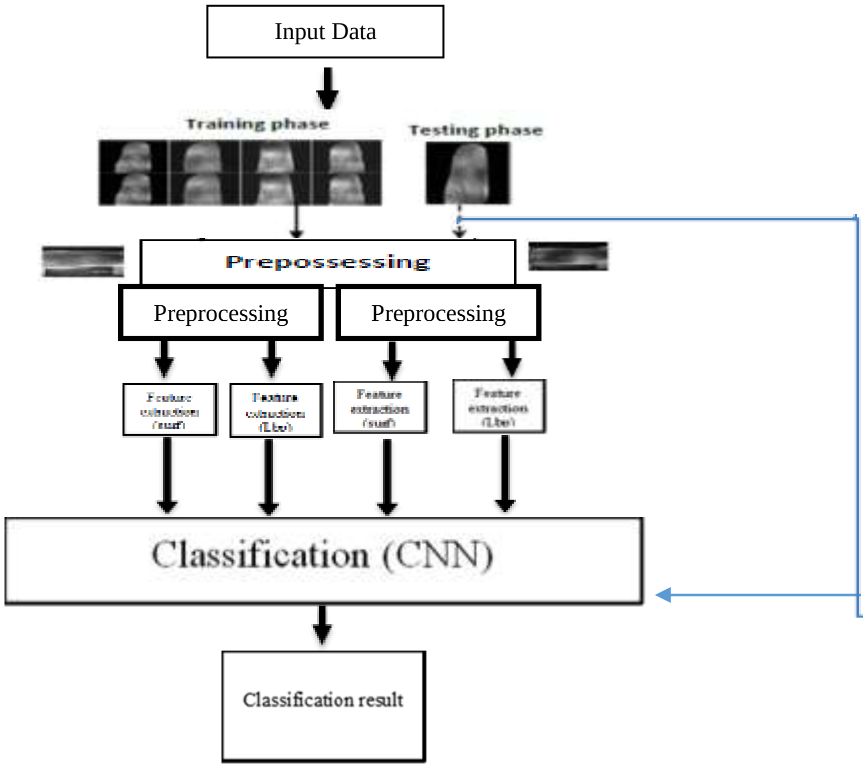


**Fig. 6 The proposed finger vein classification model based on CNN flowchart algorithm.**

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### A. Image Enhancement

Because of irregular lighting and imperfect placement of fingers during the imaging, the images are not very clear. Therefore, the finger vein images are subjected to image improvement. At first, the average gray grade of each of the overlapping blocks is studied. This average gray grade in each block is hired to eliminate the uneven illuminations in the image.

### B. Histogram Equalization

Histogram equalization is to stretch the pixel value of a picture to increase the perception data. The public histogram equalization form is (Kaur et al., 2011).

$$h(\mu) = round\left(\frac{cdf(\mu) - cdf_{min}}{(m \times n) - cdf_{min}}\right) \times (L - 1)$$

Where $cdf_{min}$ is the minimum value of the cumulative distribution function, $M \times N$ gives the image number of pixels, $L$ is the number of gray levels, and $\mu$ is the mean Enhancement for finger vein image to process Feature Extractions using 'histed' to Enhance contrast using histogram equalization and Using 'imadjust' to Adjust image intensity values or colormap and using 'adapthisteqram' to perform Contrast-limited adaptive histogram equalization.

*4.2 Finger Vein Feature Extraction (LBP + SURF)*

There is a large difference between detection and identification. Detection is finding the existence of something/object (Finding whether an object is exist in image); whereas recognition is finding the identity (Recognizing a person/object) of an object. Global options describe the image as an entire to the generalize the complete object; whereas the native options describe the image patches (key points within the image) of an object. Co-occurrence Histograms of familiarized Gradients (HOG) and Co-HOG are some samples of world descriptors. Scale-Invariant Feature remodel, (SURF), native binary patterns (LBP) some samples of native descriptors (Kaur et al., 2011).

Generally, for low-level applications like object detection and classification, world options are used and for higher-level applications like visual perception, local features are used. Combination of global and local features improves the accuracy of the recognition with the side effect of computational overheads.

*4.3 Classification using CNN Algorithm*

After scanning the input image with single unit with weights to form local receptive field and store, the outputs of first unit in its related locations in the sequenced feature map. Convolutional feature maps, add a level of invariance for translations and distortion. It includes features having decreasing order spatial resolution as complexity increases as well as globally detecting from units in the successive layers selection techniques are used for four reasons: (1) simplification of models to make them easier to interpret by researchers/users, (2) shorter training times, (3) to avoid the curse of dimensionality, and (4) enhanced generalization by reducing over fitting (formally, reduction of variance) (Garg and Parashar, 2012).

CNN methods have been developed to minimize the effect of resulting from the selection operator in the traditional NN in order to allow the parallel investigation of many solutions in the population.

## 5. Dataset

Since there is a limited number of publicly available databases for finger vein recognition, the experiments are conducted using benchmarked Finger Vein USM (FV-USM) Database (Rosdi, 2020). The database consists of the knowledge of finger vein and finger geometry with the extracted ROI (region of interest) for finger vein recognition. It is often want to verify either unimodal biometrics (finger vein and finger geometry) or bimodal biometrics (fusion of vein and geometry) systems. The images within the database were collected from 123 volunteers comprising of 83 males and 40 females, who were staff and students of University Sains Malaysia. The age of the topic ranged from 20 to 52 years old. Every subject provided four fingers: left index, left middle, right index and right middle fingers leading to a complete of 492 finger classes obtained. The captured finger images provided two important features: the geometry and therefore the vein pattern.

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Each finger was captured sixfold in one session and every individual participated in two sessions, separated by quite two weeks' time. Within the first session, a complete of 2952 (123 x 4 x 6) images were collected. Therefore, from two sessions, a total of 5904 images from 492 finger classes are gated. The locative and depth resolution of the captured finger images were 100 x 300 and 256 gray levels, respectively. Fig. 5 offers sort of finger vein images:

Vein001- 3

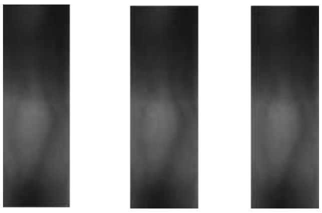

**Fig. 7 Sample of finger vein image**

## 6. Results and Discussion

Experiment: Performance accuracy CNN with different algorithm FFNN

In a typical finger vein identification scenario, the accuracy rate is the critical factor to decide the effectiveness of the approach. So, this experiment is running to validate the role of features selection module for enhancing accuracy. The adaptive features selection algorithm is implemented in this study in order to find the most important features that help to reduce the total evaluation time without the loss of accuracy. Herein, the suggested model is executed for both CNN and traditional FFNN (Feed Forward Neural Network) to performance accuracy selecting. As illustrated in Tables 1.

**Table.1 Performance accuracy CNN with different algorithm FFNN For finger vein image (Training set)**

| Algorithm | No. Feature =100 | |
|---|---|---|
| | Accuracy | Time (min) |
| **CNN** | **100 %** | **1335.11** |
| **LBP_FFNN** | **58%** | **203.46** |
| **SURF_FFNN** | **58.3%** | **2124.01** |

In this experiment for (50 person training data) we note that CNN wasn't significantly affected by the amount of features extracted and that we got a high accuracy by up 100% on the calculation of the ultimate test time reciprocally in comparison to an equivalent number of features extracted and therefore the number of coaching data FFNN that if we get a lower performance test accuracy and for all methods up 58- 58.5 %.

**Table.2 Results of proposed model identification for finger vein images (2 images for testing set)**

| | Testing data(CNN) | Training data(CNN) |
|---|---|---|
| No. of. Feature | 100 | 100 |
| Accuracy matching | 65.061 % | 99.0 % |
| Time (s) | 2.148 sec | 2.150 sec |

In Table.2. Choosing to extract features is important - the small value of Fe means that noise has a major impact on the result. When FE increases, the accuracy of the result increases highly, making it computationally expensive. Accurate detail or accuracy is very good, since the proposed model relies mainly on the Extractor Selection Module to link each image sample in a low vector that encodes the most prominent characteristics that can characterize between samples and finger vein identification by up to 99.0% in training dataset and by up to 65.06 % in testing dataset as in above a sample table for the persons Using the proposed program method CNN.

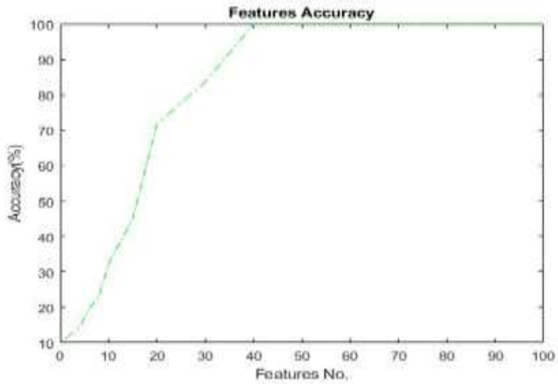


**Fig. 8 SURF features accuracy**

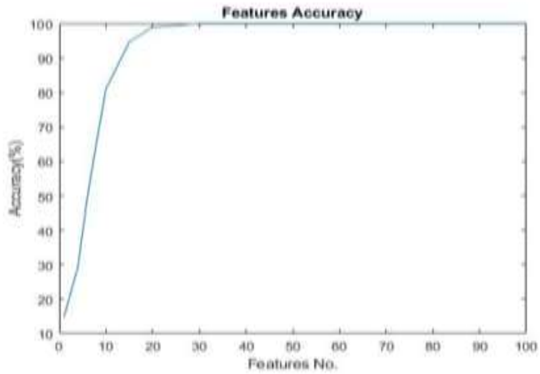


**Fig. 9 LBP features accuracy**

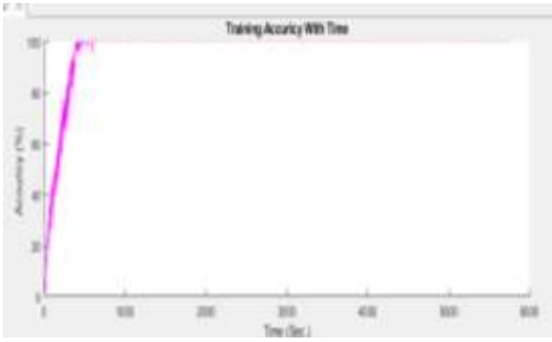

**Fig. 10 LBP (Accuracy/ time)**

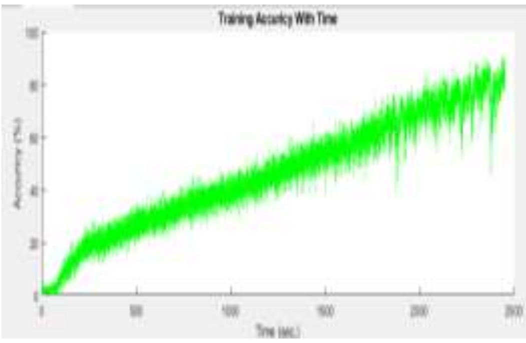

**Fig. 11 SURF (Accuracy / time)**

## 7. Conclusion

This paper has proposed an effective finger vein based personal identification model. In this work, the images were improved using local histogram equalization. This was done to enhance small object areas in the image locally that is not likely by applying a global histogram equalization method. Both the enhanced vein images gained with the assist of local and global characteristics have been fused to obtain the vein pattern based on Gabor transformation and Local pattern. This work shows that textural features are an important characteristic that can be used by finger-vein biometric systems. Although the implementation does not include any segmentation pre-processing or structural analysis of the vein pattern, obtained results are significant to demonstrate that textural features of Finger-vein images can identify people. This work also proves that textural features obtained through Gabor filter and Local Binary pattern are important discriminant characteristics in finger-vein biometric systems.

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