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Finger Knuckle Based Biometric Identifier Using Principal Component Analysis, Feature Extraction and K-NN Classifier

Ms. Sampada H. Raut[1], Mr. V. B. Raskar[2]

[1]Masters Student, Dept. of Electronics and Communication, JSPM'S Imperial College of Engineering and Research, PUNE, INDIA

[2]Professor, Dept. of Electronics and Communication, JSPM'S Imperial College of Engineering and Research, PUNE, INDIA

Abstract—*Amidst several biometric measures, the figure knuckle surface is becoming a preferred choice of researchers due to its natural ease of reproducibility and verification. For any purpose of personal identification or crime analysis, figure knuckles surface do not need to be a voluntarily presented, they get exposed naturally. Specific line pattern on the figure knuckle surfaces can be used as effective biometric measure on their own or in combination with other biometrics. Present paper demonstrates the development of a figure knuckle based biometric identification system. The system incorporates principal component analysis (PCA) for feature extraction out of pre-processed and enhanced input image as extracted from knuckle surface video capture. Secondly the system employs k-nn classifier as personal identification algorithm. The system has been tested, verified and validated with many sample test experiments. The paper illustrates the working of the system with detailed intermittent snapshots.*

Keywords—finger knuckle print, biometric identifier PCA, feature extraction, K-nnclasssifier.

I. INTRODUCTION

The word biometrics originated from Greek, where bio meant lively and metric meant measure. Thus there are some generic rules for biometrics. These are universality, permanence and measurability. Firstly, it is its universality in nature. Universality means every normal human being must possess the biometric. Like the commonly used biometrics, e.g. iris, fingerprints, ear surfaces etc. are identified to be with any normal human personality. Secondly, the permanence means the time invariance of the human biometric feature. For example, the fingerprints do not change over the time or age of the person. So one can use them to identify or authenticate irrespective of age of the subject. Lastly, it is the measurability of the biometric. Measurability means the biometric can be extracted by means of a system, in a form of information which can be further processed, compared or stored as and when needed. For example the personal iris colored structure can be verified with the stored ones.

At the earliest like 500 B.C. fingerprints on clay slabs were used as the authorizing signatures of a trader as found recorded in Babylonian trade records. This could have been the firsts of known use of biometrics in the human history. However, it can be very well said that the mankind learnt to make use of biometrics much earlier, perhaps from the age of first human generations. That time primarily the facial identification is practiced for personal identity. As the human society grew, so the population went high. Humans started living small clusters doing trades across. And the facial identification didn't make much sense for personal authentication. Then they developed the signature system. A ring or stamps were the initial specialized instruments but when it came to generic purpose and absolute true authentication fingerprints became the biometric solution to identification.

The objective of present work is to implement the finger knuckle print image as the bio-metric identifier. Here, Principal Component Analysis (PCA) an appearance based method is used for the feature extraction from knuckle surface and these extracted features are classified using*k-nn* classifier which is robust classifier for authentication process. Different parameters such as mean, standard deviation, coefficient of variance, skewness, entropy, smoothness, homogeneity, contrast, correlation and kurtosis are used to make the system more robust.The objectives of the system to be so developed are:

- To achieve biometric identification of a person using Finger Knuckle Print.
- To explore alternate method for verification other than traditional methods for robust classification.
- To achieve automated approach for biometric identification.
- To make system user friendly and cost effective.

II. RELATED WORK

Even before to look at the systems using finger knuckles as effective biometric, let's seek the baseline information regarding the finger knuckles. As illustrated in Fig. 1, the fingers are connected with palm bone structure through means of phalanx. These small bones i.e. phalanges (plural to phalanx) constitute the fingers. The fingers bend at the inter-phalangeal joints. The back surface of the inter-phalangeal joints as it appears with texture and lines is the very knuckle surface used as the biometric.

In 2005, Woodard and Flynn [6] presented a novel approach for personal identification, which utilizes finger surface features, primarily the knuckles as a biometric identifier. This was first of its kind of system utilizing finger knuckle surfaces as the biometric. They calculated the curvature-based surface representation, shape index, for the index, middle, and ring fingers using dense range data images of the hand. This representation was used for comparisons to determine subject similarity. Their experiments involved the use of a large data set of range images collected over time. They also examined the performance of individual finger surfaces as a biometric identifier as well as the performance when using the three finger surfaces in conjunction. The results of experiments indicated that this approach performed well for this system with knuckle biometric.

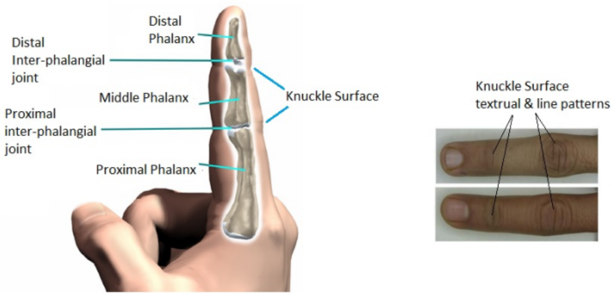

Fig. 1: Illustration of finger anatomy and knuckle surfaces

In another parallel effort on using knuckle as biometric identifier it would be worthwhile mentioning the works by Kumar and Ravikanth [7][8]. Firstly in 2007 [7] and then in 2009 [8] tried to present their results on their developed knuckle based biometric system as they tested it out with a large subject datasets. They investigated the system based on texture of the hand knuckles. The texture pattern generally produced by the finger knuckle bending is highly unique and makes the surface a distinctive biometric identifier. They tried to combine it with hand geometry biometric system to seek the performance improvement using two biometric. Hand geometry features were acquired from the same image, at the same time and integrated to improve the performance of the system. The finger back surface images from each of the users were used to extract scale, translation and rotational invariant knuckle images. Their proposed system, especially on the peg-free and non-contact imaging setup, achieved promising results when tested over a database of 105 users as they reported in the article.

Further in 2009, Zhang et al. [9] presented a new approach to online personal authentication using finger knuckle-print (FKP), which has distinctive line features. They claimed to have developed a cost-effective FKP system, including a novel image acquisition device and the associated data processing algorithms. To efficiently match the FKPs, they proposed a Band Limited Phase-Only Correlation (BLPOC) based FKP matching method. They conducted extensive experiments and demonstrated the efficiency and effectiveness of their proposed technique. They commented that comparing with other existing finger back surface based systems, their proposed FKP authentication has merits of high accuracy, high speed, small size and cost-effective. Unlike other systems as developed by this time which used to capture the entire hand camera image and then extract out the knuckle images, this system directly captures the knuckles area image only.

In 2006, Sricharan et al. [10] investigated the possibility of using the knuckle as a biometric trait for user authentication. They as well extracted the knuckle regions from the hand images and used correlation methods for the purpose of verification. Their experimental results on a data set of 125 people showed that the finger knuckle surfaces are a viable biometric trait, which can be used as an alternative to finger and palm prints or in conjunction with them.

Very recently in 2012, Choras and Kozik [11], presented their developments in palm print segmentation and feature extraction for human identification are presented. Moreover, they also presented a new approach to knuckle biometrics. They showed that both palm print and knuckles features may be considered as very promising biometric modalities which can be used in contactless human identification systems. As they illustrated, their goal was to propose efficient algorithm that could run on mobile devices. However, in the paper they showed the results for palm print and knuckles biometrics, but on separate databases. But now they working on creating multimodal hand–palm–knuckle database acquired by mobile phones cameras in unrestricted (real-life) conditions. They claimed that their methods can be used in mobile biometrics scenario since mobile end-terminals portfolio has exploded with devices providing greater functionality and usability with more processing power on board. It was estimated that by 2015 all the sold mobile handsets will be "smart" which more of the truth looks now days. They also forecasted that biometric human identification using contactless unsupervised images would very soon become important application. Kumar [13] in a conference in 2012 on biometrics theory and application, iterated that biometric identification using finger knuckle imaging has generated lot of promises with interesting applications in forensics and remote biometrics. Prior efforts in the biometrics literature have only investigated the `major' finger knuckle patterns that are formed on the finger surface joining proximal phalanx and middle phalanx bones. However, he investigated the possible use of `minor' finger knuckle patterns which are formed on the finger surface joining distal phalanx and middle phalanx bones. He commented that the `minor' or `upper' finger knuckle patterns could either be used as independent biometric patterns or employed to improve the performance from the major finger knuckle patterns.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The architectural system diagram is shown in Fig.2. As depicted Fig.2, there are two data flow paths for the system as designed. The first data flow path is for training data set and the secondary for test data. The training data set is comprised of knuckle feature extraction using principal component analysis (PCA) and maintained within the system in form of training data.

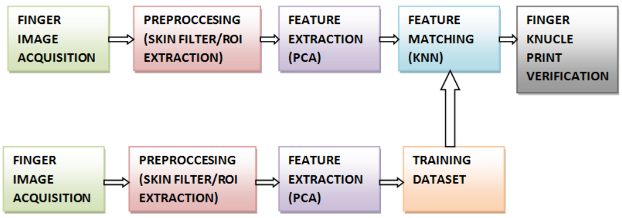

Fig. 2: System architecture for finger knuckle based identification system

The inflow process for each training data is same as a random test data. Both, the training as well as the test data, i.e. figure knuckle images had to go through the pre-processing step to enhance, zoom and focus the knuckle line patterns prior to feeding to PCA system for feature extraction purposes. The figure knuckle surface is fed to the system via an input video camera, as also shown in the photograph in Fig. 3. Once the training data is populated the system is ready to accept the test data for biometric matching of knuckle surface line patterns. This is achieved through *k-nn* (k-nearest neighbor search) algorithm used as the classifier herein the system.

1. Database Acquisition

For data input, subject figure is video captured using a video web camera with white platform as evidently demonstrated from photograph in Fig. 3.

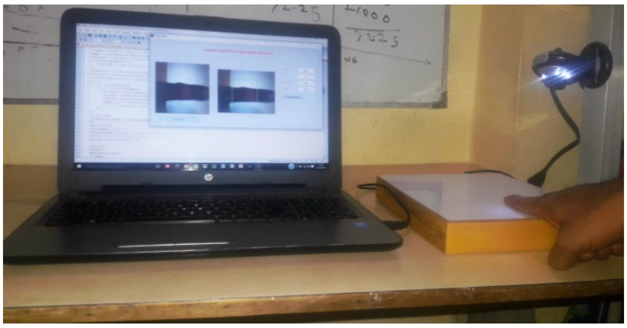

Fig. 3: System set-up demonstrating data input

The web camera being used employs a high quality CMOS image sensor, producing the image resolution of 25M pixels. The camera uses color saturation image control to produce the RGB24 or equivalent I420 quality image. The video capture of knuckle images are captured by the camera at frame rate of 30 fps (frames per second) through the lens (f = 6.0).

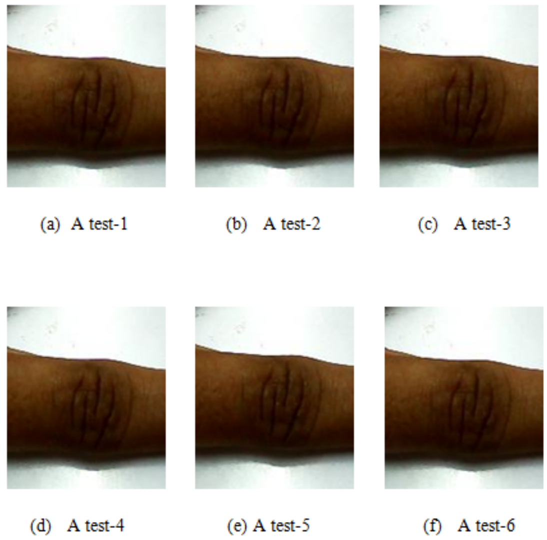

Fig. 4: Knuckle samples collected of same subject six times for training database.

For training data acquisition, in prior six different subjects volunteered. For each subject knuckle video capture, multiple distinct images are accepted/inputted toassure the accuracy of the training data independent on the finger positioning, light etc. factors. For example, Fig. 4 shows the six different snapshots of a single subject knuckle surface image samples. These samples are stored in the training database under the same class tagged by the subject personality.

2. Pre-processing

It can be understood that the systems overall performance would depend on the input image quality and its readiness or betterness for feature extraction. Thereby, once the input image is accepted, it undergoes through some image pre-processing such as, extraction, skin filtering, grayscale conversion and histogram equalization. The

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system at present uses MATLAB's image processing and filtering utilities for the purpose. A skin filter defines explicitly (using a number of rules) the boundaries the skin cluster has in a color space. Single or multiple ranges of threshold values for each color space component are created and the image pixel values falling within these range(s) for all the chosen color components are defined as skin pixels.Genric steps in skin filter algorithm are as

1. Start
2. Input : Image using RGB or HSV color map
3. For each pixels of the image :
    a. New Pixel : Pi
    b. If Pi match range of pixels
        i. It lies in regions of pixels of image.
        ii. Else Pi does not lie in the regions of images.
    c. Repeat for each image map in various color models.
4. End

The resulting image is enhanced using ROI (Region of Interest) for ease of use. The image enhancement is done using gray scale conversion and subsequently, histogram equalization technique. For the present developed system GUI demonstrates the intermittent pre-processing results in Fig. 5. The enhanced image then becomes ready for the extraction of the image features.

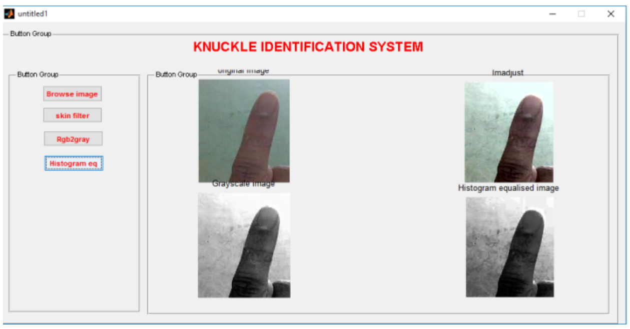

Fig. 5: Pre-processing of finger knuckle image

In MATLAB,the histogram equalization seeks to flatten your image histogram. Basically, it models the image as a probability density function (or in simpler terms, a histogram where you normalize each entry by the total number of pixels in the image) and tries to ensure that the probability for a pixel to take on a particular intensity is equiprobable (with equal probability).Figure 6 illustrates the working principle behind the histogram equalization with a sample photograph.

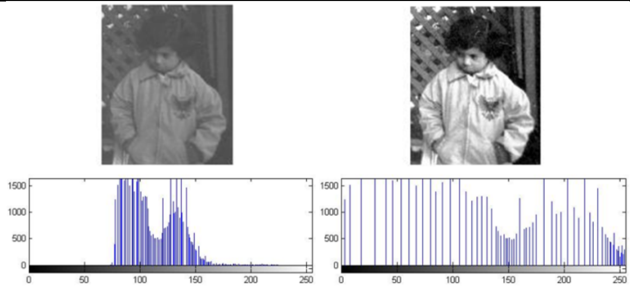

Fig. 6: Illustration of histogram equalization

The premise behind histogram equalization is for images that have poor contrast or images that look like theyare too dark, or if they are too washed out, or if they are too bright are good candidates for a developer to apply histogram equalization. If one plots the histogram, the spread of the pixels is limited to a very narrow range. By doing histogram equalization, the histogram will thus flatten and give you a better contrast image. The effect of this with the histogram is that it stretches the dynamic range of your histogram.

3. Feature Extraction Using Principal Component Analysis (PCA)

The Principal component analysis (PCA) is a very well know computational methodology for statistical analysis of a given data system moreover PCA is also finding its application in pattern recognition tools for the systems commonly used for face recognition or finger print recognition for that matter. Moreover one has to appreciate the fact that when it comes to a large dimensional data PCA finds its most suitable application for pattern recognition of such data. PCA extract information from a knuckle image [Principal Components] and encodes that information in a suitable data structure. In mathematical terms we find Eigen vectors and Eigen values of a covariance matrix of images. Here, one image is just a single point in high dimensional space [n × n], where n × n are the dimensions of image.

But we are only interested in principal Eigen vectors because these can account for substantial variations among a bunch of images. They can show the most significant relationship between the data dimensions. Eigenvectors with highest Eigen values are the principle component of the image set. Using these set of Eigen vectors we can construct Eigen knuckles.

Algorithm for finding Eigen knuckles for M knuckle images having similar dimensions is explained as below.

1. Collect a bunch of sample knuckle images (say three knuckle images for each person). Dimensions of all images should be same say $N_X \times N_Y$. An image can be stored in an array of $(N_X \times N_Y) \times 1$ dimension [Γ] which can be considered as an image vector. Therefore training set of image vectors of size $(N_X \times N_Y) \times M$ is,

$\{\Gamma_i | i = 1,2, \dots \dots , M\}$

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Where, M is the average number of images. To find the average image of bunch of images,

$$\psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i$$

2. To find the deviated $[Img_1 - Avg, Img_2 - Avg, \dots \dots, Img_n - Avg\ ]$ images

$\phi_i = \Gamma_i - \ \psi \mid i = 1,2, \dots \dots, M$

3. Calculate the covariance matrix.

$$C = AA^T$$

$$C = \begin{bmatrix} c(1,1) & \dots & c(1,d) \\ \vdots & \ddots & \vdots \\ c(d,1) & \dots & c(d,d) \end{bmatrix}$$

Where, $A = [\phi_i, \dots, \phi_m]$

But the problem with this approach is that we may not be able to complete this operation for a bunch of images because covariance matrix will be very huge.

For example matrix of covariance for a knuckle image of size $N_X \times N_Y$ pixels is of size$(P \times P)$, P being $(N_X \times XN_Y)$. This covariance matrix is very hard to work with due to its huge dimension causing computational complexity. It is very hard or may be practically impossible to store that matrix. Also finding that matrix will require considerable computational requirements. So for solving this problem we first compute the matrix L.

$L = A^T A$

And then find the Eigen Vectors [V] related to it

$$V_X(X = 1, \dots \dots \dots, M)$$

Eigen Vectors for covariance matrix C can be found by

$U = [u_1, \dots \dots \dots, u_m]$

$\quad = [\emptyset_1, \dots \dots \dots, \emptyset_m][v_1, \dots \dots \dots, v_m]$

$\quad = A \cdot V$

Where $U_X(X = 1, \dots \dots \dots, M)$ are Eigen Vectors for C.

Using these Eigen vectors, we can construct Eigen knuckles. Eigen knuckle will have numerical value which will be classified and identified using K-nearest neighbor classifier.

4. Classification And Identification Using K-nn Classifier

Classification is the process of detecting a pattern and comparing it with the predefined pattern in the database and identifies the matching features. Training has to be done to the predefined features and the trained and test features are compared. The test feature is our input image.When the features match, and then it is recognized. Here, the *k-nn*classifier is used. K-nearest neighbor classifier is a robust method used for matching. The k-nearest neighbor (*k-nn*) pattern classifier is an effective learner for general pattern recognition domains

In *k-nn* classification, an object is classified by its k nearest neighbors (k is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of that single nearest neighbor.

Suppose sample in data set has n elements that we grouped to form an n-dimensional vector:

$x = (x_1, x_2, \dots \dots, x_n)$

These n attributes are considered to be the independent variables. Every sample is extra attribute, denoted by *y* (the dependent variable), whose assessment depends on the other *n* attributes *x*. We assume that *y* is a categorical variable, and there is a scalar function, *f*, which assigns a class, *y* = *f*(*x*) to every such vectors. We suppose that a set of *T* such vectors are given together with their corresponding classes: *x*(*i*), *y*(*i*) for *i* = 1,2, ...,*T*. This set is stated to as the training set. The idea in k-Nearest Neighbor methods is to identify *k* samples in the training set whose independent variables *x* are similar to *u*, and to use these *k* samples to classify this new sample into a class.

The KNN classification needs the Euclidean distance calculation between nearest points and is given by

$$d_2(a_1, a_2) = \sqrt{\sum_{j=1}^{k}\left(a_{1,j} - a_{2,j}\right)^2}$$

Here $a_1$and a_2 are two different points.

The advantage in KNN is that higher values of *k* provide smoothing that reduces the risk of over-fitting due to noise in the training data. Also, training done is very fast and no loss of information.

IV. RESULTS AND DISCUSSIONS

The system thus proposed has been developed within the MATLAB environment and functions from the same platform. The start time system GUI is displayed in Fig. 8. The “Start Video” button initiates the input intake.

The system had been then subject to testing for finger knuckle based biometric personal identification for several subjects, randomly chosen, who may or may not volunteered for the training data set inputs. For each subject the index finger major knuckle surface has been video graphed through the system camera input. The images of knuckle surfaces of such test subjects then underwent pre-processing, where the exact knuckle surface image portion was extracted from the video frames. Following which the surface pattern image enhancements achieved by grayscale conversion and histotrophic equalization, as also discussed in brief in earlier section.

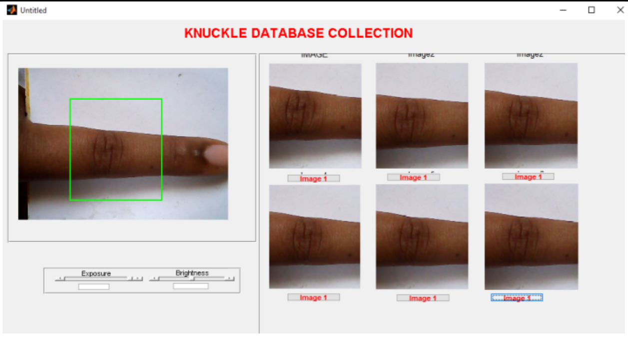

Fig. 7: System GUI for database collection

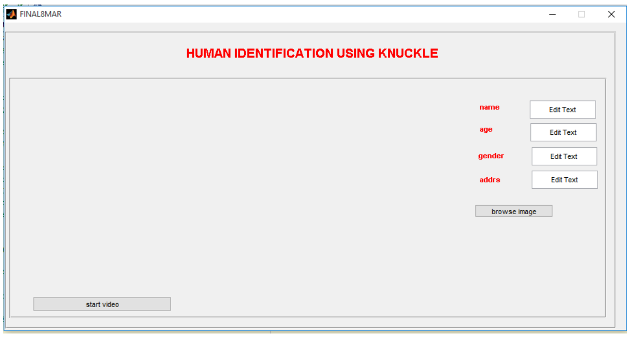

Fig. 8: System GUI

The system extracted the features using PCA module as implemented and thereafter, *k-nn*classifier searches round through the existing training dataset figures out the exact match of the knuckle surface line patterns of subject to one of instance from the stored database in infinitesimally small time. As also demonstrated in the system final GUI image, in Fig. 9, the system presents the input subject query knuckle image and also the matching instance knuckle image from the database on successful final personal identification.

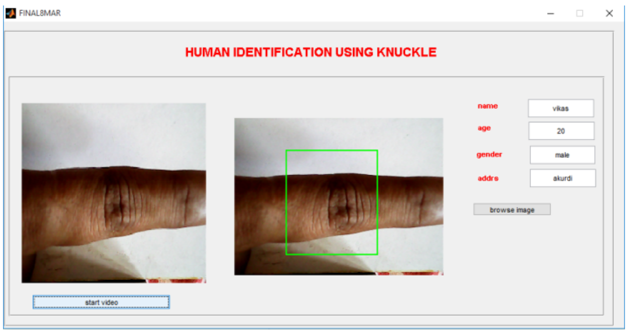

Fig. 9: Final GUI

Various statistical features such as mean, standard deviation, variance and covariance are calculated for the testing experiments. This work has also implemented extraction of other features in addition to the Eigen value and features mention above. Following Table I summarize these statistical features as observed from the text experiments.

Table I: Statistical Features Extraction

Mean	**129.5216**
Standard deviation	73.3174
Entropy	-0.4856
Smoothness	-0.0827
Skewness	-0.0025
Contrast	1.0000
Kurtosis	0.2070
Homogeneity	0.0403
Variance	0.5362
Correlation	16.1904

V. CONCLUSION

In resent work, the system for finger knuckle based biometric identifier has been ingeniously developed. The novelty of the work includes successful implication of appearance based method, namely,principal component analysis (PCA) for feature extraction and use of *k-nn*classifier as identification method for knuckle based biometrics. The system makes use of image pre-processing employing techniques like skin filter, grayscale conversion and histogram equivalence. The overall system performance as tested had been found satisfactorily accurate. The system response time and performance is comparably fast to that of many state of the art systems as reported in literature. Also, the system testing which had been efficiently carried out with limited training dataset at present can be very well scaled to order of magnitude larger data points.

The system developed at present; make use of single major knuckle surface as biometric identifier. Going forward combined use of both knuckle surfaces as biometric measure can enhance the system performance to superior levels.

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