A New Finger Vein Verification Method Focused On The Protection Of The Template

Khamis A Zidan 1 and Shereen S Jumaa 2
1 Professor, Researcher Al-Iraqia University, Iraq
2 Al-Nahrain University, College of Information Engineering, Iraq

Email: khamis_zidan@aliraqia.edu.iq
Email: shireen.sadiq81@gmail.com

Abstract: This paper examines a collection of finger vein enhancement stages that have not only low computational complexity but also high distinguishing capacity. This proposed series of enhancement stages is based on the equalization of fuzzy histograms. A mixture of Hierarchical Centroid and Gradient Histograms was used to extract features. Both the enhancement stages were evaluated using 6 fold stratified cross validation with K Nearest Neighbor and Support Vector Machine (SVM). Experimental results show that the (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm which can be used to solve problems of classification and regression. Calculations of KNN in the test data are highly accurate. Using stratified 6-fold analyzes on all fingers of all hands in the collected database, when selecting the right and middle fingers based on the analysis of the 106 people in the data set. Compared with SVM and related works, the algorithm proposed has optimum performance.

Keywords: Finger vein, median filter, KNN, DNN, HOG

1. Introduction
The utilization of biometric innovations rules data security of this age and day—the procedure of recognizing an individual dependent on natural highlights, for example, physical or conduct attributes [1]. Visual biometrics incorporate iris, hand morphology, eyes, unique mark, and so on and walk, articulation, signature, keystroke design, and so forth. A large number of these highlights are defenseless against hacking endeavors, [2] [3] which has prompted the advancement of more solid biometrics, for example, vein designs in the finger [4] hand [5] and palm [6]. These are practically difficult to manage without the authorization of the clients, and consequently more hard to copy. In this paper another strategy for improving finger vein information will be introduced. Vein information must be gotten from a living body and can in this manner not be acquired from a dead body [7]. Under the skin lies the vascular framework, and it is likewise hard to watch [8] without exceptional hardware, for example, infrared radiation and video, and so forth. The gracefully chain is contactless, so wellbeing is ensured and item comfort is ensured. Most cutting edge finger vein acknowledgment techniques experience the ill effects of the downsides related with the extraction of highlights because of bad quality pictures and helpless perceivability of the vein. Bad quality pictures can be because of low control of infrared radiation, low lighting conditions and light scattering in tissues covering the vein structure to be captured[6]. Entanglements can likewise happen on account of corpulent fingers, low surrounding temperature or inadequately constructed catch equipment[7]. Another boundary which enormously hampers the cycle is that a dominant part of such calculations rely upon boundaries
which can't be set over various information bases as a characterized norm. Changes in finger direction in information from preparing and exploration can likewise significantly affect division based tests just as factual strategies.

2. Database
It is all around concurred that SDUMLA-HMT is the hardest finger vein information base to preprocess [9] as appeared in Fig.1. The clarifications for this non-ideality are as per the following:

1. The picture quality isn't acceptable [10]
2. Contrasted with the overall picture scale, the finger area is little [10].
3. Pictures differ from revolution to interpretation to move [11]

A hazardous technique for catching pictures was presented.

![Figure 1. Database SDUMLA-HMT-sample data.](image)

This is the explanation we chose this information base for our calculation approval. A sum of 106 individuals have partaken in its assortment. The gathered pictures are in the configuration of.bmp. Good and left hands utilized [12]. The left, center and ring finger information were gathered for each hand and 6 examples were gotten for each finger as appeared in Table 1. The framework used to this end was created by Wuhan University’s Joint Lab for Intelligent Computing and Intelligent Systems.

| Parameter         | Information |
|-------------------|-------------|
| Maximum people    | 106         |
| Hands / person    | 2           |
| Hand fingers      | 3           |
| Finger images     | 6           |
| Image resolution  | 320 × 240   |
| Total database size | 0.85 b      |

3. Technique
The procedure utilized comprises of just a couple of chosen basic improvement administrators that are anything but difficult to execute and computationally light however joined in an arrangement as appeared in Fig.2. They have a profoundly itemized upgraded picture of the finger vein and highlight extraction and order stages.
4. The steps of method presented as follows

4.1 Detection of finger

Pictures from the information base are gathered by setting close infrared radiation onto the eye. The veins retain this radiation due to the development of deoxygenated hemoglobin and consequently seem hazier than the encompassing tissue [13] as appeared in Fig.3.
The initial step is to distinguish and trim this picture into the finger field. Cover channel was utilized after the system endeavored for this restriction by [14] Texture is eliminated after the finger zone has been standardized. Cover is made on the premise that in examination, the finger district is lighter than the remainder of the area of the picture. Utilizing a veil channel [14], the approach of was utilized to find the finger region. The region of the fingers was standardized and surface eliminated from it. This depends on the possibility that the district of the finger is hazier than the area of the foundation, as it goes through infrared light. The cover used to fragment an information base picture's finger territory is near the pictures as appeared in Fig. 4:

Figure 4. Masks to find the finer regions of the images being collected. (a) Mask for identification of the upper finger area. (b) Mask for the identification of the lower finger area.

For each value along the x axis, the finger boundary is identified by computing the masking value in y axis. The point at which this masking value is maximized is actually the finger boundary in y direction [15] Before that, the image of the database is cropped by maintaining only those rows that are fully white on the corresponding mask as shown in Fig. 5.

Figure 5. (a) Database image, (b) Cropped finger.

4.2 Gamma correction

Since the finger trimmed is dark, the subsequent stage is to expand its splendor with Gamma adjustment [16] [17]. This works by expanding the dynamic scope of pixel forces by controlling the pixels in a nonlinear way. It's cultivated by diminishing co-event network homogeneity. This plans to hold the basic subtleties to the surface and make them more conspicuous [18] [19]. It significantly improves picture quality by coordinating normal picture brilliance the ideal way. For the calculation proposed, it was seen that if the gamma boundary is held to 2, Gives the best presentation as appeared in Fig. 6.
4.3 Vein sharpening

While the gamma-revised adaptation of the picture is preferable brilliant over the first picture, there is still extension for development with regards to the unmistakable quality of the veins. The unsharp veiling calculation is utilized to hone the picture to additionally draw out the vascular structure. It is accomplished in order to upgrade the differentiation between various pixel power ranges [20]. It brings some visual perspectives which would some way or another have been overlooked by the natural eye to the closer view [21]. The honing of pictures doesn't deliver any subtleties, it just improves the concealed highlights and surface of a picture. The cycle begins by delivering an "unsharp" rendition of a picture, or obscured one. This variant is then deducted from the first so as to recognize edge presence. The differentiation is then expanded specifically along the recognized edges bringing about an a lot more keen variant of the picture [22].

The unsharp cover that we actualized for our investigations is created utilizing a Gaussian channel to spatially channel the upgraded finger vein picture adaptation of the gamma. Standard deviation of the Gaussian low pass channel is the boundary which controls the territory around the edges which is improved during the honing cycle. The importance in applied strategy was held at 4. A more prominent worth impacts a larger aspect of the encompassing territory, and the other way around. During tests honing power was likewise held to be 4[22].

4.4 Double Histogram Equalization

The subsequent stage was to play out an evening out of the histogram to change the dissemination of pixel powers. We picked a double histogram adjustment with the qualities of Fuzzy Histogram Equalization and Cumulative Histogram Equalization. The basic point of utilizing histogram balance is to disseminate the histogram of pixel force all the more similarly so as to expand the dynamic scope of pixels which in actuality improves contrast. The complete balance of the histogram was done first. This was joined by a balance of the Fuzzy histogram [23].

5. Cumulative histogram equalization

The cumulative equalization of the histogram of an image is performed as in equ. (1) By the following steps [24]:

1. Obtain histogram of the image.
2. Get cumulative distribution function histogram.
3. For each gray value of the original image, using histogram equalization formula to find a new corresponding value.

If:

Complete number of pixels= N
Total range of acceptable degrees of intensity = L
Then [25],

\[ S_k = \frac{L}{N} \times C_R (k) - 1 \] (1)
Here the initial intensity value is in an integer ranging from 0 to $L-1$, and $S_k$ is the mapped intensity value. Replace each gray value from the original image with the corresponding newly determined value from the step above.

Vein sharpening gives the image as seen in Fig.8 (a) before cumulative histogram and Fig.8 (b) after Cumulative Histogram equalization.

Fig.7 (a) An image before cumulative histogram, (b) after Cumulative Histogram equalization.

6. Fuzzy histogram equalization

Brightness preserved dynamic fuzzy histogram equalization manipulates the histogram of the image in such a way that there is no peak remapping. It redistributes the histogram values uniformly only between two consecutive peaks in valley-areas. It contains the some steps in[25]. Fuzzy statistics can manage the inaccuracy of gray values much better than conventional crisp histograms and thus produce a smooth histogram as shown in Fig.8. A fuzzy histogram is a series of real numbers $h(i)$, $i \in \{0, 1, \ldots, L-1\}$ where $h(i)$ is the frequency of existence of gray levels that are “around i”. Each gray value $l(x,y)$ is measured a fuzzy number $l~(x,y)$ as shown in equ.(2). Fuzzy histogram is then calculated as:

$$h(i) \leftarrow h(i) + \sum_y \sum_i \mu_{l(x,y)}(i), \quad k \in [a, b] \quad (2)$$

Here in equ.(3) $\mu_{l(x,y)}(i)$ is the triangular fuzzy membership function assumed by:

$$\mu_{l(x,y)}(i) = \max [0, 1 - \frac{|l(x,y)-i|}{4}] \quad (3)$$
7. Median filtering

In this nonlinear cycle, the picture prepared by twofold histogram evening out is at that point made to go through a middle channel to eliminate hasty commotion and salt and pepper clamor. A window is utilized for choosing neighboring pixels for each column. At that point the middle power an incentive inside this window is determined for the pixels, and that worth is doled out to the pixel on which the activity was performed. For all pixels of the picture this progression is rehashed [26]. It holds the edge-data subsequently diminishing commotion easily. Middle channel quality relies upon window size [27]. We utilized 3x3 window size for the examinations of this exploration as appeared in Fig.9.

It soothes the texture irregularities as shown in Fig.10 image:

8. Power law

A final step was to apply power law transformation to the image to improve contrast and enhance visibility. The transformation of power law is expressed by equ. (4) [28]:

\[
\text{Neighbourhood values are} \\
115, 119, 120, 123, 124 \\
125, 126, 127, 130 \\
\text{Median is 124}
\]
\[ S = CR^\gamma \] (4)

Here \( C \) and \( \gamma \) are positive constants. \( \gamma \) may be a positive value below or more than 1. For \( C=1 \), if \( \gamma < 1 \) then the input image is converted to an image with a broader pixel intensity range and if \( \gamma > 1 \) then the image is changed by representing it into a contracted range of pixel [29].

Experimental research has shown that the approach presented is not only reliable in efficiency but also produces state-of-the-art results in negligible time as shown in Table 2. For this aim of our experiments, we kept \( C=1 \) and \( \gamma=0.3 \). The power law in this technique curves with fractional values of \( \gamma \) mapped the median-filtered finger vein to a changed image. Enhanced final image as shown in Fig.11.

Figure 11. After Power law

9. Feature extraction
9.1 HOG Feature extraction
In troublesome visual circumstances, Histogram of Directed Gradient (HOG) extraction work is widely utilized due to its capacity to do well in those circumstances [30]. It extricates data about the circulation of target edges and is a helpful device for structure recognizable proof [31] [32] [33] [34]. [35] [36]. This low-level capacity descriptor doesn't affect changes and item turns. Its calculation fills in as follows:

i. Image is separated into little parts that are called cells.

ii. For every phone, edge arrangement indications are determined in the neighboring nearby area (for 'marked inclinations,' histogram channels are uniformly spread more than 0-360 and for 'unsigned' more than 0-180) [37].

iii. Lighting impact is set to scaling the histogram tallies. To do as such, apply the energy metric over the bigger related parts for every nearby histogram.

iv. In the end, trademark vector is gathered by having all includes of direction the deliberate prevailing way of inclinations.

In this manner, the previously mentioned advances standardize the square cells whose joint histograms build up the total picture's HOG include vector. Scaling and pivot have no impact on the calculation, as just the central issues are utilized for extraordinary scale-space location [37]. The slope bearings for an example picture fix are appeared in Fig.12 beneath:
Thus, the HOG descriptor primarily consists of features concerning histograms of object edges of an image.

The descriptor HOG function can be defined by the equation (5) [38]:

\[ V_{HOG} = [F_1, F_2, F_3, \ldots, \ldots, F_k] \]  

(5)

Where:

K = the overall number of overlying blocks in an image

Fi is the normalized block vector of i-th block:

\[ F_i = [h_{1,i}, h_{2,i}, h_{3,i}, \ldots, h_{C \times B, i}] \]  

(6)

Where:

C= overall number of cells in a block

B= overall number of bins in a cell

Bins generate a cell and cells structure a block.

For a sample image of size 32 x 32, this process can be established as below in Fig.13 [38]:

Figure 13  (a) Sample image (b) Gradient visualization. Each block (red outline) comprises four cells (white outline) (c) Process of generating vector HOG function [38]

9.2 Hierarchical Centroid Shape Descriptor (HCSD)

HCSD [39] [40] is fixed inkd-tree process decomposition [41]. It is a descriptor of features mainly for forms. Centroid coordinates extracted from a binary image create a descriptor of this element. It works by iteratively disintegrating an image through thekd-tree algorithm into sub-blocks of pixels. It includes data concerning centroid coordinates of local parts [42]. If d denotes the depth of the extraction functions, the length of this descriptor will be defined by \(2 \times (2d - 2)\).
Adopt $I$ is the $M \times N$ binary image. Its foreground is represented by $I_{fg}$ and background by $I_{bg}$. HCSD is then shaped with the following stages [41]:

i. For input $I$, find its transpose: $I^T$.
ii. Catch centroid $C(x_c, y_c)$ at the root level for each separate input:

$$x_c = \frac{m_{10}}{m_{00}}$$  \hspace{1cm} (7)
$$y_c = \frac{m_{01}}{m_{00}}$$  \hspace{1cm} (8)

Where:

$m_{10}$ = first order moment along the x-axis
$m_{01}$ = the first order moment along the y-axis
$m_{00}$ = area of $I_{fg}$

Raw moment (also recognized as the time of order $(p+q)$) is specified for a 2D continuous function $f(x, y)$ by:

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy$$  \hspace{1cm} (9)

The raw moments $m_{pq}$ of a digital image with pixel intensities $I(i, j)$ are detailed by:

$$m_{pq} = \sum_{i=0}^{M} \sum_{j=0}^{N} i^p j^q I(i, j)$$  \hspace{1cm} (10)

iii. The image is decomposed into two sub-images according to its centers of gravity $(x = x_c, y = y_c)$ before the desired depth of breakdown is reached. Changing the axis of secured coordinates is needed at each next point.

iv. As the next step, it is important to scale the vector reached to a range of -0.5 to 0.5. Here, 0 is for the centroid root-level. Negative range represents the decomposition of the tree on the left side, and positive range on the right side.

v. Ultimately, extracted image I and IT features are combined. K-tree structure of decomposition as shown in Fig.14

![Figure 14 K-tree decomposition construction [41].](image-url)
10. Classification

1. K nearest neighbors

K-Nearest Neighbor classifier, also called KNN [43] is a primitive but immensely favored classification method. The label of K closest samples is assigned to a test feature vector [44] [45]. It is a non-parametric passive algorithm [46]:
   ➢ It is termed “non-parametric” as it does not cause any inherent assumptions about the placement of data into classes.
   ➢ It is termed “passive” because it does not utilize training data for generalization. It forecasts test data based on all the training data.

2. Support Vector Machine (SVM)

Support vector machine (SVM) is an administered framework for characterizing at least two gatherings. This is utilized in various order situations, for example, recognizable proof of transcribed examples, pictures, pictures, text and significantly more. It has a wide application in picture arrangement, since it can effectively order pictures. It has been broadly utilized in clinical science for characterizing cells. Double characterization is basic on the grounds that the outcome is either 0 or 1, and exceptionally productive outcomes can be gotten from any traditional AI calculation, however a calculation is required for multi-class order that can group such classes as important. In the Fig. 15 shows two items to characterize [47].

![Figure 15: Two objects to classify][47]

Hyperplane is a dividing line, separating groups. Objects lying in each class depend on the score of confidence, which is high for objects far from hyperplane, while objects near hyperplane have low score of confidence. May translate this confidence score into probability. The position of the hyperplane is determined using equation [47]:

\[
\text{sign}(ax + by + c)
\]

Constants a, b and c decides the position of hyperplane.

Probabilities for every set of points is given by equation [47]:

\[
\sum_{i=1}^{N} P[y_i = x_i] = \frac{1}{1 + \exp(-1(ax_i + by_i + c))}
\]

Use the log function values is optimal, and for categorization the highest likelihood value is used. If the equation is multiplied by -1, the cost function will become the equation [47].
\[ \sum_{i=1}^{N} -\log(1 + \exp(-1(ax_i + by_i + c))) \]

In SVM margins on both sides of the hyperplane are drawn, and there is no point between the margins and the hyperplane. The equations below of hyperplane and margins are [47]:

\[
\begin{align*}
    w \cdot x - b &= 0 \\
    w \cdot x - b &= 1 \\
    w \cdot x - b &= -1
\end{align*}
\]

Dot product shows normal vector, x is the point and there is offset of the hyperplane that goes from the origin to the normal vector. The kernel method replaces the dot product in the hyperplane equation. These kernel functions are:
1) Radial Basis Function
2) Sigmoid
3) Polynomial

11. Results

The computational time for each stage of the proposed enhancement methods is presented in table 2 below.

| Preprocessing Stage                  | Average time taken (seconds) |
|--------------------------------------|------------------------------|
| Finger detection                     | 0.0072                        |
| Gamma correction                     | 0.0011                        |
| Image sharpening                     | 0.0036                        |
| Cumulative Histogram Equalization    | 0.0028                        |
| Fuzzy Histogram Equalization         | 0.0031                        |
| Median filtering                     | 0.0066                        |
| Power Law transform                  | 0.0014                        |
A broad evaluation of the calculation was directed. For each capacity extraction technique and furthermore for every classifier, any conceivable mix of finger type and hand type has been checked. The center finger for the considered dataset of 106 people was discovered to be the most discriminative of all. Each finger for each hand is viewed as an alternate classification for the test results recorded underneath, despite the fact that it is of a similar person.

![Figure 16 Finger identification and finger testing GUI](image)

Acknowledgment and confirmation results for right, left and both hand center finger are summed up in the table below (3,4,5). Results for KNN are given with HOG, HC and joined element vector HOG and HC. Supporting vector machines calculations are executed with three pieces for each component extraction model which incorporates straight, Gaussian and polynomial as talked about already. The consequences of these portions shifted as appeared in Table 6, starting with one element extractor technique then onto the next. The precision of HOG and joined HOG+HC techniques is close, and most extreme exactness for the polynomial bit strategy is accomplished.

### Table 3  Results of KNN with right hand, middle finger

| Method                           | Accuracy (%) | EER (%) |
|----------------------------------|--------------|---------|
| Proposed approach using CHFHE with HOG | 98.1132      | 0.0178  |
| Proposed approach using CHFHE with HC | 98.1132      | 0.0178  |
| Proposed approach using CHFHE with HOG+HC | 98.1132      | 0.0178  |
Table 4 Results of KNN with left hand, middle finger

| Method                                    | Accuracy (%) | EER (%) |
|-------------------------------------------|--------------|---------|
| Proposed approach using CHFHE with HOG    | 96.2264      | 0.0356  |
| Proposed approach using CHFHE with HC     | 94.3396      | 0.0534  |
| Proposed approach using CHFHE with HOG+HC | 96.2264      | 0.0356  |

Table 5 Results of KNN with both right and left hand, middle finger

| Method                                    | Accuracy (%) | EER (%) |
|-------------------------------------------|--------------|---------|
| Proposed approach using CHFHE with HOG    | 96.6981      | 0.0178  |
| Proposed approach using CHFHE with HC     | 95.7547      | 0.023733|
| Proposed approach using CHFHE with HOG+HC | 96.6981      | 0.0178  |

Table 6: SVM Results
15

| SVM Linear | SVM Gaussian | SVM Polynomial |
|------------|--------------|---------------|
| HOG        | 0.85         | 0.1           |
| HC         | 0.1          | 0.7           |
| HOG + HC   | 0.85         | 0.1           | 0.9           |

12. Conclusion and future work

In this paper a novel strategy for finger vein improvement has been introduced for the motivations behind ID and check. The discoveries are altogether tried with KNN and furthermore with SVM. KNN’s forecasts on test information demonstrated considerably more exact. Utilizing delineated 6-overlap investigation on all hands fingers in the SDUMLA information base, with an EER of 0.0178 a greatest exactness of 98.1132 has been accomplished. In view of the investigation of the 106 people in the dataset, the most prejudicial finger was the right-hand center finger. It very well may be accepted from the previously mentioned discoveries that KNN beats SVM by a generally wide edge. Explanation behind this can be because of the way that SVM is substantially more appropriate for issues with not so much information but rather more time required. Examination can be done later on by modifying the length of this decreased dimensionality and furthermore by exploring different avenues regarding different techniques, for example, Principal Component Analysis (PCA) [48] . What's more, it is additionally conceivable to utilize Convolutional Neural Networks [49] to follow yield utilizing move learning methods.

References

[1] Syazana-Iqtan K, Syafeeza AR, Saad NM, Hamid NA and Saad WM., "A review of finger-vein biometrics identification approaches," Indian J. Sci. Technol, vol. 9, 2016.
[2] Marcel S, Nixon MS and Li SZ, Handbook of biometric anti-spoofing, New York: Springer, 2014.
[3] Menotti D, Chiachia G, Pinto A, Schwartz WR, Pedrini H, Falcao AX, Rocha A., "Deep representations for iris, face, and fingerprint spoofing detection.," IEEE Transactions on Information Forensics and Security, no. 864-79, 2015.
[4] Kumar A and Zhou Y, " Human identification using finger images," IEEE Transactions on image Processing, no. 2228-44, 2014.
[5] Wen X, Zhao J and Liang X., "Research on enhancing human finger vein pattern characteristics," in In2010 Asia-Pacific Conference on Power Electronics and Design 2010 May 30, IEEE.
[6] Lee EC and Park KR., "Image restoration of skin scattering and optical blurring for finger vein recognition," Optics and Lasers in Engineering, no. 816-28, 2011 Jul 1:49(7);
[7] Yang L, Yang G, Yin Y, Xi X., " Finger vein recognition with anatomy structure analysis.," IEEE Transactions on Circuits and Systems for Video Technology, no. 1892-905., 2018
Aug;28(8).

[8] Meng X, Xi X, Yang G, Yin Y., "Finger vein recognition based on deformation information.," Science China Information Sciences. 2018, 2018 May 1;61(5):052103.

[9] Abdulsahib, G. M., & Khalaf, O. I. (2018)., "Comparison and Evaluation of Cloud Processing Models in Cloud-Based Networks.," International Journal of Simulation--Systems, Science &Technology, 19(5).

[10] Yang L, Yang G, Yin Y, Xi X., "Finger vein recognition with anatomy structure analysis," IEEE Transactions on Circuits and Systems for Video Technology., 2018 Aug;28(8):1892-905.

[11] Yang Y, Yang G, Wang S., "Finger vein recognition based on multi-instance.," International Journal of Digital Content Technology and its Applications. , no. 86-94., 2012 Jun;6(11).

[12] Kim W, Song J, Park K. "Multimodal Biometric Recognition Based on Convolutional Neural Network by the Fusion of Finger-Vein and Finger Shape Using Near-Infrared (NIR) Camera Sensor.," Sensors., 2018 Jul;18(7):2296.

[13] Akintoye KA, Rahim MS, Abdullah AH. , "Challenges of Finger Vein Recognition System: A Theoretical Perspective.," ARPN Journal of Engineering and Applied Sciences, 2018..

[14] Lee EC, Lee HC, Park KR. , "Finger vein recognition using minutia-based alignment and local binary pattern-based feature extraction.," International Journal of Imaging Systems and Technology., no. 179-86., 2009 Sep;19(3).

[15] Park KR, Jang YK, Kang BJ., "A study on touchless finger vein recognition robust to the alignment and rotation of finger.," The KIPS Transactions: PartB. 2008;15(4):275-84..

[16] Amiri SA, Hassanpour H. , "A preprocessing approach for image analysis using gamma correction.," International Journal of Computer Applications., 2012 Jan;38(12):38-46..

[17] Somasundaram K, Kalavathi P. , "Medical image contrast enhancement based on gamma correction.," Int J Knowl Manag e-learning. , 2011 Jan;3(1):15-8.

[18] Khamis A.Zidan and Shereen S.Jumaa, "An Efficient Enhancement Method for Finger Vein Images Using Double," International Journal of Advanced Science and Technology, vol. 29, pp. 996-1006, 2020.

[19] Khamis A.Zidan and Shereen S.Jumaa, "Finger Vein Recognition using Two Parallel Enhancement Approaches," Periodicals of Engineering and Natural Sciences, vol. 7, no. 2303-4521, pp. 514-529, 2019.

[20] Hassanpour H, Samadiani N, Salehi SM., "Using morphological transforms to enhance the contrast of medical images.," The Egyptian Journal of Radiology and Nuclear Medicine. , 2015 Jun.

[21] Kansal S, Purwar S, Tripathi RK. , "Image contrast enhancement using unsharp masking and histogram equalization.," Multimedia Tools and Applications., 2018 Oct 1:1-20.
[22] X. T., "The application of adaptive unsharp mask algorithm in medical image enhancement.," in In Proceedings of 2011 Cross Strait Quad-Regional Radio Science and Wireless Technology Conference 2011 Jul 26 (Vol. 2, pp. 1368-1370.), IEEE.

[23] Khamis A. Zidan and Shereen S.Jumaa, "A Highly-verified biometric recognition system using an ultra-speed specifically developed finger vein sensor," Periodicals of Engineering and Natural Sciences, vol. 7, no. 2303-4521, pp. 1539-1545, November 2019.

[24] Garg P, Jain T. A., "Comparative Study on Histogram Equalization and Cumulative Histogram Equalization.," International Journal of New Technology and Research.;3(9).

[25] Sheet D, Garud H, Suveer A, Mahadevappa M, Chatterjee J., "Brightness preserving dynamic fuzzy histogram equalization.," IEEE Transactions on Consumer Electronics., no. 2475-80., 2010 Nov;56(4).

[26] Nagu M, Shanker NV., "Image de-noising by using median filter and weiner filter.," International Journal of Innovative Research in Computer and Communication Engineering., 2014 Sep;2(9).

[27] Makandar A, Halalli B., "Breast cancer image enhancement using median filter and CLAHE.," International Journal of Scientific & Engineering Research., 2015;6(4):462-5.

[28] Janani P, Premaladha J, Ravichandran KS., " Image enhancement techniques: A study.," Indian Journal of Science and Technology., 2015 Sep;8(22):1-2.

[29] Rajkumar S, Malathi G., "A comparative analysis on image quality assessment for real time satellite images.," Indian J Sci Technol., 2016 Sep;9:1-1.

[30] S. A. Korkmaz, A. Akçiçek, H. Bınol and M. F. Korkmaz, "Recognition of the stomach cancer images with probabilistic HOG feature vector histograms by using HOG features," in 2017 IEEE 15th International Symposium on Intelligent Systems and Informatics (ISYS), 2017.

[31] J. Ouyang, "Combining Extreme Learning Machine, RF and HOG for Feature Extraction," in IEEE Third International Conference on Multimedia Big Data (BigMM), 2017.

[32] S. A. Korkmaz, A. Akçiçek, H. Bınol and M. F. Korkmaz, "Recognition of the stomach cancer images with probabilistic HOG feature vector histograms by using HOG features," in IEEE 15th International Symposium on Intelligent Systems and Informatics (ISYS), 2017.

[33] J. Chen, D. Zhou, Y. Wang, H. Fu and M. Wang, "Image feature extraction based on HOG and its application to fault diagnosis for rotating machinery.," Journal of Intelligent & Fuzzy Systems, 2018.

[34] C. Q. Lai and S. S. Teoh, "Efficiency Improvement in the Extraction of Histogram Oriented Gradient Feature for Human Detection Using Selective Histogram Bins and PCA.," in 9th International Conference on Robotic, Vision, Signal Processing and Power Applications , 2016.

[35] A. Vashaee, R. Jafari, D. Ziou and M. Mehdi Rashidi, "Rotation Invariant HOG for Object Localization in Web Images," Signal Processing, 2016.
[36] C. Hang, F. Hu, A. E. Hassanien and K. Xiao, "Texture-based rotation-invariant Histograms of Oriented Gradients," in 11th International Computer Engineering Conference (ICENCO), 2016.

[37] O. Deniz, G. Bueno, J. Salido and F. D. I. Torre, "Face recognition using Histograms of Oriented Gradients," Pattern Recognition Letters, 2011.

[38] Y. Ma, X. Wu, G. Yu, Y. Xu and Y. Wang, "Pedestrian Detection and Tracking from Low-Resolution Unmanned Aerial Vehicle Thermal Imagery," Sensors, 2016.

[39] S. Armon, "Handwriting Recognition and Fast Retrieval for Hebrew Historical Manuscripts," Hebrew University of Jerusalem, 2011.

[40] A. T. K. W. A. Sexton, "Font recognition using shape-based quad-tree and kd-tree decomposition," in Proceedings Of The Joint Conference On Information Sciences, 2000.

[41] E. Ilunga-Mbuyamba, J. G. Avina-Cervantes, D. Lindner and J. Guerrero-Turrubiate, "Automatic brain tumor tissue detection based on hierarchical centroid shape descriptor in Tl-weighted MR images," in 2016 International Conference on Electronics, Communications and Computers (CONIELECOMP), 2016.

[42] L. K. J. H. K.-H. J. Wahyono, "Similarity-based classification of 2–d shape using centroid-based tree-structured descriptor," Modern Advances in Applied Intelligence, Springer International Publishing, 2014.

[43] S. Zhang, X. Li, M. Zong, X. Zhu and R. Wang, "Efficient kNN Classification With Different Numbers of Nearest Neighbors," IEEE Transactions on Neural Networks and Learning Systems, 2018.

[44] A. Z. A. Zainuddin, W. Mansor, L. Y. Khuan and Z. Mahmoodin, "Classification of EEG Signal from Capable Dyslexic and Normal Children Using KNN," American Scientific Publishers, 2018.

[45] M. S. Sarma, Y. Srinivas, M. Abhiram, L. Ullala and M. S. Prasanthi, "Insider Threat Detection with Face Recognition and KNN User Classification," in IEEE International Conference on Cloud Computing in Emerging Markets (CCEM), 2017.

[46] R. S. P. S.Ponnmani, "Classification Algorithms in Data Mining – A Survey," International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2017.

[47] P.Batta, "Evaluation of Support Vector Machine Kernels for Detecting Network," Anomalies, 2019.

[48] Y. Aït-Sahalia and D. Xiu, "Principal Component Analysis of High-Frequency Data," Journal of the American Statistical Association, 2017.

[49] M. Jamal, A. Arun, RossaErik and M.Shapirob, "On automated source selection for transfer learning in convolutional neural networks," Pattern recognition, 2018.

[50] D. Sheet, H. Garud, A. Suveer, M. Mahadevappa and J. Chatterjee, "Brightness Preserving
Dynamic Fuzzy Histogram Equalization, "IEEE Transactions on Consumer Electronics," 2010.

[51] M. Nagu and N. Shanker, "Image De-Noising By Using Median Filter and Weiner Filter," International Journal of Innovative Research in Computer and Communication Engineering, 2014.

[52] A. Makandar and B. Halalli, "Breast Cancer Image Enhancement using Median Filter and CLAHE," International Journal of Scientific & Engineering Research, 2015.

[53] F. Bahmaninezhad and J. H. Hansen, "Generalized Discriminant Analysis (GDA) for Improved i-Vector Based Speaker Recognition," INTERSPEECH, 2016.

[54] P. Sun, W. Feng, R. Han, S. Yan and Y. Wen, "Optimizing Network Performance for Distributed DNN Training on GPU Clusters: ImageNet/AlexNet Training in 1.5 Minutes," Distributed, Parallel, and Cluster Computing, 2019.