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Finger knuckle pattern person identification system based on LDP-NPE and machine learning methods

Ali Mohsin Aljuboori[1,2], Mohammed Hamzah Abed[1]
[1]Department of Computer Science, College of Computer Science and Information Technology, Al-Qadisiyah University, Qadisiyyah, Iraq
[2]Biocomputing Research Center, School of Computer Science and Technology, Harbin Institute of Technology, Heilongjiang, China

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ABSTRACT

Biometric-based individual distinguishing proof is a successful strategy for consequently perceiving, with high certainty, an individual's character. The utilization of finger knuckle pictures for individual ID has shown promising outcomes and produced a ton of interest in biometrics. By seeing that the surface example delivered by twisting the finger knuckle is profoundly particular, in this paper we present a new biometric validation framework utilizing finger-knuckle-print (FKP) imaging. In this paper, another methodology in view of neighborhood surface examples is proposed. Local derivative pattern (LDP) histogram is investigated for FKP description. Then based on neighborhood preserving embedding (NPE) is used for dimension reduction to the feature vector. The feature extraction method is computed and evaluated in the identification framework task. The machine learning methods (multiclass support vector machine (MSVM), random forest (RF), k-nearest neighbor (KNN)) are proposed for classification. The system is tested on the PolyU finger knuckle database. The empirical results proved that the proposed model has the best results with RF. Moreover, our proposed LDP-NPE model has been evaluated and the results show remarkable efficiency in comparison with previous work. Experimentally, the proposed model has better accuracy as reflected by 99.65%.

Corresponding Author:

Ali Mohsin Aljuboori
Department of Computer Science, College of Computer Science and Information Technology
Al-Qadisiyah University
Qadisiyyah, Iraq
Email: ali.mohsin@qu.edu.iq

1. INTRODUCTION

Individual verification is ordinary mindfulness to the two enterprises and scholastic examination because of its various applications. Biometrics can be utilized to recognize people in light of their physical and social attributes and can function as an optimal answer for this issue. In the beyond thirty years, numerous biometric properties have been proposed, such as unique mark, face, iris, retina, palm-print, hand calculation, voice, stride and mark, and finger knuckle [1].

- Overview

Among the current biometric characteristics like special finger impression, face, iris, palmprint, and voice, critical interest has been paid to hand-based biometrics in view of their high client affirmation. The palm print, hand math, palm surface, finger vein, and hand vein have been for the most part especially considered. Lately, the internal and the outer knuckle surfaces have been proposed and investigated as unique hand-based quality. In view of its adaptability and constancy, the skin configuration surface finger knuckle-print (FKP), around the phalangeal joint of each finger. Normally, the model skin course practically the phalangeal joint, which are around inverse to each finger, are our goal line features [2].

The quick expansion in the utilization of online business capacities and harshness of data innovation into occasional life needs solid client recognizable proof for compelling and got admittance control. Finger knuckle print-based biometrics has gotten extensive consideration over late years which takes advantage of a few inner and outer elements that are very unmistakable in a person. The client acknowledgment for the hand-based biometrics framework is extremely high. The finger knuckle surface possesses unique patterns that have been utilized in personal identification, the major challenge is how to use physical features to identify person [3].

- Problem statement and challenges

Numerous challenges have appeared with biometric identification deployments using fingerprints. The low exactness of the finger impression matching because of the standard skin distortions, leftover soil, sweat, dampness, or potentially scars, is notable while an enormous number of unskilled workers and older people likewise be reestablished from fingerprints with not exactly OK quality for the acknowledgment. The finger knuckle examples can be all the more helpfully imaged from a good way, dissimilar to fingerprints, as the significant wrinkles and bent examples are effectively apparent with unaided eyes [4].

The FKP skin is much arch and results in rough reflection which also appeared shadow. The FKP images have low contrast and uneven illuminations [5]. The 2D finger knuckle pictures have the actual design of the skin wrinkle designs between the center and proximal phalanges of the fingers. An assortment of strategies utilizing the finger knuckle pictures has been portrayed in the writing for biometrics-based individual acknowledgment. Because of the idea of component descriptors, these procedures can be profoundly sorted into three classifications; those in light of subspace learning, unearthly elements, and those because of the discretization of neighborhood highlights. All through these, those approaches given the discretization of nearby highlights stand out in the writing as such strategies create smaller size formats, which give quicker recovery or coordination [4].

- Related work

The researchers in [5], [6], proposed a way to deal with individual validation utilizing 2D finger-back surface imaging. They execute a framework to catch hand-back pictures and afterward separated the finger knuckle area by some preprocessing steps. The learning strategies, for example, principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA) were joined to make include extraction and coordinating. Kumar and Zhou [7] proposed the hearty line direction code to separate the direction of the finger knuckle surface pictures. According to Shariatmadar and Faez [8] the scientist introduced an FKP acknowledgment plot for individual recognizable proof and character confirmation. The technique encodes the neighborhood paired design local binary pattern (LBP). Each picture deteriorates in a few squares, each square is convolved with a bank of gabor channels and afterward, the LBPs histograms are separated from the convolved pictures. At long last, a BioHashing technique is applied on the got fixed-length include vectors.

Attia *et al.* [9] proposed technique, for the information finger knuckle, two sorts of elements (i.e., binarized factual picture elements and gabor filer bank) are extricated, which are then taken care of to fluffy principles-based multi-facet profound rule classifier to decide if the client is real or faker. Morales *et al.* [10] applied a Gabor channel to improve the FKP data and a scale-invariant component change (filter) to extricate the elements. Tarawneh *et al.* [11] give an FKP framework in light of the VGG-19 profound model to remove profound highlights from FKP pictures. The removed highlights are gathered from the VGG-19 model's layer 6 and layer 7. Then, at that point, applying consolidating highlights from various layers and performing dimensionality decrease utilizing head part examination (PCA). Malik e*t al.* [12] the specialist executes FKP confirmation. They propose a lattice projection technique for removing line highlights from the finger-knuckle print for the individual check. Ordinarily, all the level and the upward knuckle lines are separated by projecting the knuckle print picture onto a shift-and-distinction lattice. The surface and lines of FKP are separated and utilized for individual validation. They proposed a Watchful element extraction strategy and a sliding window matching technique is applied on FKP. Attia *et al.* [13] proposed a binarized factual picture highlights to extricated from every single locale in FKP. The elements extricated are intertwined. The combination is trailed by dimensionality decrease step utilizing head part examination and straight discriminant investigation to work on its biased power. In light of cosine Mahalanobis distance for matching stage is executed. Jaswa and Poonia [14] investigated normalizing the recognized round palm or finger knuckle and subsequently apply line ordinal model. The non-crushed quaternion wavelet gives denser part depiction at various scales and headings when taken out over proposed cut encoding and fabricates the isolation power of line and edge features. Then, a blend of backtracking search estimation and 2D2LDA has been used to pick the overarching palm and knuckle features for grouping. A technique consolidating worldwide elements and neighborhood highlights for the acknowledgment of FKP pictures presented by [15].

The primary part investigation was utilized as the worldwide component and the neighborhood double example was taken as the nearby element to remove the surface highlights. The combination of worldwide and neighborhood highlights depends on a two-layer sequential combination strategy. Research by Anbari and Fotouhi [16] a biometric confirmation framework for FKP surface given loosened up neighborhood ternary example is introduced. To expand the presentation, falling, covered fixing, and uniform pivot invariant example choices are proposed. Vidhyapriya and Lovelyn [17] proposed a technique for biometrics validation utilizing FKP. The surface examples from finger knuckle are separated utilizing gabor with exemption boost calculation and the component vectors from these surface examples are procured utilizing scale invariant feature transform (SIFT) algorithm. Research by Usha and Ezhilarasan [18] the mathematical and surface highlights are separated for finger knuckle. The rakish mathematical investigation is extricated as mathematical highlights that remove precise based include data for acknowledgment. The surface component extraction in light of finished nearby ternary example age strategy, 2D log gabor channel technique and fourier scale-invariant element change strategy are joined to infer the neighborhood surface highlights of an obtained finger back knuckle surface. In this paper some of features extraction methods have been used to increase the efficiency and performance of proposed model based on local derivative pattern (LDP), neighborhood preserving embedding (NPE), and machine learning tools.

- Paper layout

This paper is organized as following: in second section the proposed model is iullustrate in details, starting from features extraction to final decision, then some of experimental result are dicussed with analysis of the achieved performance, finally conclusion of all work is iullustrate.

2. PROPOSED SYSTEM

The proposed algorithm in this paper is based on local feature extraction. The overall architecture of a typical FKP recognition system is to read an FKP image and divide it into several blocks then compute the LDP features to all the blocks and create the feature vector, then based on histogram matching compute the performance to the system. On the other hand, applied the NPE method to dimension reduction and proposed a machine learning method to compute the recognition accuracy as shown in Figure 1.

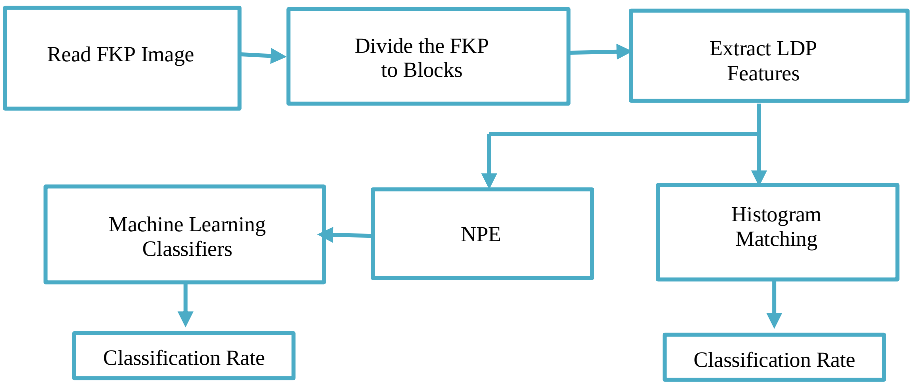

Figure 1. Proposed system

2.1. Feature extraction

Equations should be placed at the center of the line and provided consecutively with equation numbers in parentheses flushed to the right margin, as in (1). The use of microsoft equation editor or MathType is preferred. Feature extraction is an interaction that distinguishes significant elements or qualities of the information. It expands the exactness of gained models by extricating highlights from the information. This period of the overall structure lessens the dimensionality of information by eliminating the repetitive information. In the proposed framework the LDP highlights are utilized as a nearby picture descriptor. The LDP highlights consider relative edge reaction values in eight headings around a pixel to encode the nearby neighborhood property of the picture pixel with a double piece arrangement.

LDP administrator, which encodes directional data in the area instead of force, gives out an eight pieces parallel code to the focal pixel of an information 3×3 grayscale picture fix. The paired code is made by convolving the grayscale sub-picture of 3×3 with Kirsch covers in eight distinct headings (M0-M7) [19]. The Kirsch masks=KM*i*, *i*=0,..,7 are shown in Figure 2.

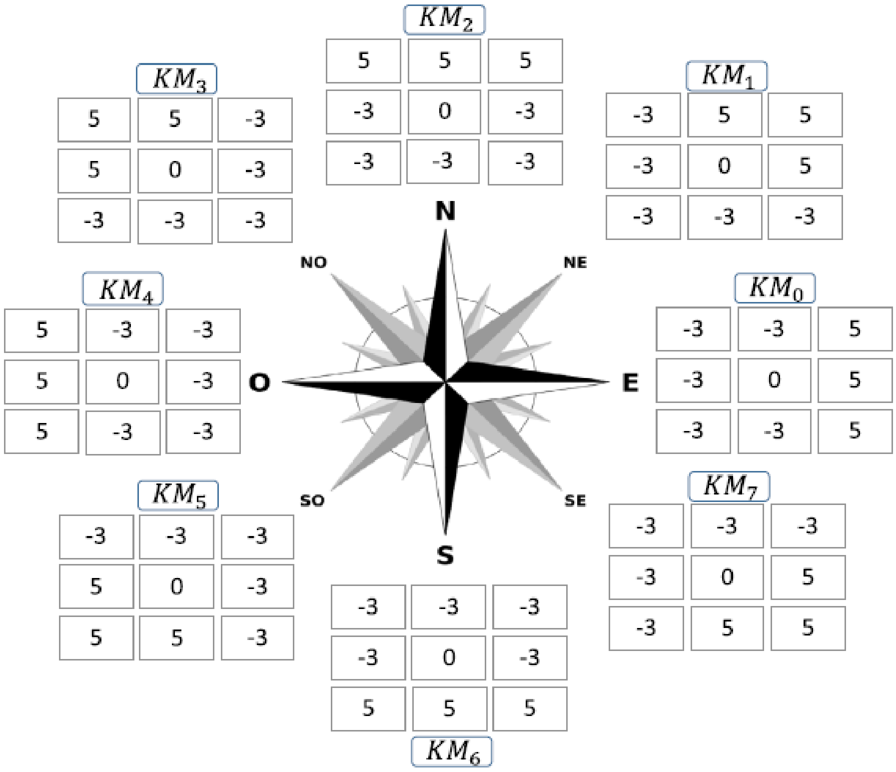

Figure 2. Kirsch masks in eight directions [19]

In the proposed calculation as [20]-[24], the LDP administrator processes the subsidiary course variety data that is viewed as second-request design credits. All adjoining pixels add to the example code with the course of its subsidiary for the subordinate of the middle point. The subsidiaries are conscious of the same bearings as 0, 45, 90 and 135 degrees were thought of. The image derivatives in each direction are obtained by subtracting neighboring pixels according to the direction as (1).

$$\begin{aligned} I'_{0^\circ}(Z) &= I(Z_0)-I(Z_4) \\ I'_{45^\circ}(Z) &= I(Z_0)-I(Z_3) \\ I'_{90^\circ}(Z) &= I(Z_0)-I(Z_2) \\ I'_{135^\circ}(Z) &= I(Z_0)-I(Z_1) \end{aligned} \tag{1}$$

The neighbors Z1, Z8 are considered according to Figure 3 around a center pixel Z0. The direction compliance with the derivative value at the center point is encoded for every neighbor as (2).

$$code = \sum_{i=1}^{8} f\left(I'_{\propto}(Z_0), I'_{\propto}(Z_i)\right) 2^{8-i} \tag{2}$$

Z_1	Z_2	Z_3
Z_8	Z_0	Z_4
Z_7	Z_6	Z_5

Figure 3. 8-neighborhood considered in LDP

This operation is repeated for each considered derivative direction as (3):

$$f\left(I'_{\propto}(Z_0), I'_{\propto}(Z_i)\right) = \begin{cases} 0 & I'_{\propto}(Z_0) * I'_{\propto}(Z_i) > 0 \\ 1 & I'_{\propto}(Z_0) * I'_{\propto}(Z_i) \le 0 \end{cases} \tag{3}$$

where i=1, 2, ..., 8 are the indices of the neighbors. The LDP pattern code for a given direction is the concatenation of the bits corresponding to each neighbor as (4).

$$LDP_{\propto}^{2}(Z_0) = \{(I'_{\propto}(Z_0), I'_{\propto}(Z_1), .., (I'_{\propto}(Z_0), I'_{\propto}(Z_8)\} \quad (4)$$

2.2. Neighborhood preserving embedding

NPE is a significant direct dimensionality decrease technique that works at safeguarding the nearby complex design [25]. Less number of highlights are simpler to make due. It's basic for the models to prepare, store, and furthermore simple for representation. In fact, you can take out a portion of the first highlights or qualities. Different DR methods have been carried out for extending high-layered information into low-layered portrayal. The current strategies normally protect either just the worldwide design or neighborhood construction of the first information, however not both [26], [27]. In contrasts space installing, each example is planned into a vector space in light of its difference to different examples. The primary component of this strategy is that any uniqueness method, whether metric or non-metric, euclidean or non-euclidean, symmetric or topsy-turvy, can be utilized [28]. The NPE algorithm proposed in [29], [30] is proposed used in our work.

2.3. Macinine learning methods

Machine learning is planning calculations that permit a PC to learn. Learning does not take acknowledgment yet learning is a substance of finding factual equity or different examples in the information. Hence, several machine learning strategies will somewhat be like how people could method a learning task. Then again, learning calculations can convey perception into the overall difficulty of learning in various conditions. About design acknowledgment frameworks, characterization is essential in figuring out which structure has a place with which class. Characterization is the principle objective to relegate the example to obscure pre characterize classes in light of their portrayals as boundaries [31]. Machine learning is implemented to learn machines how to work with the data more efficiently. Sometimes after displaying the data, it is difficult to understand the efficient information from the data [32]. In the proposed system, we suggest three methods for classification (multiclass support vector machine (MSVM), random forest (RF), and k-nearest neighbor (KNN)).

2.3.1. Multiclass spport vector machine

It is one of the most powerful self-learning algorithms; which is developed from statistic-learning to be used for big data regression and classification. The first type of support vector machine (SVM) is proposed for the twofold order issue. Notwithstanding, in a climate, is expected to isolate multiple classes simultaneously. MSVM acts in true applications, for example, picture arrangement, biometrics, written by hand character acknowledgment, and so on, and is presently one of the standard devices for AI and information mining. In the issue of multi-class order, the worry turns out to be more complicated in light of the fact that the results could be more than one class and should be isolated into N fundamentally unrelated classes. There are far to tackle multi-class grouping issues for SVM, the two most well-known procedures are the one-against one classifier and one-versus all classifier [33], [34]. In our proposed framework the calculation that is utilized is introduced in [33].

2.3.2. Random forest

Feature subset determination turns out to be vital and overwhelming on account of information esteems those have with a bigger number of factors. An arbitrary backwood is the assortment of order trees. The arrangement tree might be known as a choice tree, is the production of a tree that comprises of the individuals from the class variable on its leaf hubs and the elements of other ward factors live on the middle of the road hubs [35]. The proposed calculation that recommends in our paper is recorded in [36].

2.3.3. K-nearest neighbor

KNN is one of the directed learning techniques. KNN technique expects the comparability between the new case/information and accessible cases and places the new case into the classification that is generally like the accessible classes. KNN calculation saves all the predefine information and groups another information variable because of the likeness. At the point when new information comes, it tends to be effortlessly characterized into a comparative classification by utilizing KNN calculation. The algorithm that suggests in our work is listed in [37].

3. EXPERIMENTAL RESULT

In this section, we describe the databased content and we tested two experiments. The first one was without dimension reduction and applied the histogram matching and the second experimental applied with dimension reduction with several machine learning methods.

3.1. Databased description

To look at the presentation of the proposed 2D finger knuckle acknowledgment structure. The HKPolyU 3D finger knuckle pictures data set is an as of late accessible benchmark that has a two-meeting data set with 2D and 3D finger knuckle pictures. This database has 2D images for the forefinger and middle finger to the 190 subjects on two sessions. The 190 subjects captured six images for the forefinger and other six images for the middle finger in each session. The total image that is used for the forefinger is 2,280 (190 persons*12 images) and the same number for middle finger 2,280 images [4], [38].

3.2. Experimental

The primary test for the proposed framework as displayed in Figure 1, is histogram coordinating. In the ID task, the histogram removed from the question picture is contrasted with every one of them put away histograms to figure out which one it is generally like. The closest neighbor search with the histogram convergence distance metric is applied to decide character among selected people. The general distinguishing proof framework execution is recorded in Table 1 for the proposed tried dataset.

Three classifiers are applied to predict the finger knuckle pattern. These classifiers are MSVM, RF, and KNN. Each classifier is applied individually on the feature that reduced by NPE method. In KNN, the number of neighbors (K) has been used in evaluating the performance accuracy of the model is set to one to reduce the noise (increase the probability of the close neighbors). Table 2 shows the results for the classifiers when split the data to 50% training and 50% testing. Table 3 shows the result when split the data to 63% training and 37% testing.

Table 1. Accuracy based histogram marching

Finger	Accuracy (%)
Forfinger	93.947
Middle finger	94.956

Table 2. Accuracy of FNK classification based LDP-NPE (50% train, 50%test)

Finger	Accuracy	Sensitivity	Specificity	Precision	F1_score	Matthews correlation coefficient	Kappa	False positive rate	Method
Forefinger	0.975	0.975	0.999	0.990	0.978	0.980	0.573	1.2992e-04	MSVM
Middle finger	0.974	0.974	0.999	0.995	0.981	0.983	0.588	1.3452e-04	MSVM
Forefinger	0.974	0.974	0.999	0.984	0.975	0.977	0.595	1.3694e-04	KNN
Middle finger	0.985	0.985	0.999	0.989	0.985	0.986	0.276	7.6582e-05	KNN
Forefinger	0.996	0.996	0.999	0.996	0.996	0.996	5.29e+12	4.217e-05	RF
Middle finger	0.996	0.996	0.999	0.996	0.996	0.996	5.29e+12	4.637e-05	RF

Table 3. Accuracy of FNK classification based LDP-NPE (63% train, 37%test)

Finger	Accuracy	Sensitivity	Specificity	Precision	F1_score	Matthews Correlation Coefficient	Kappa	False positive rate	Method
Forefinger	0.992	0.992	0.999	0.995	0.992	0.993	0.246	4.177e-05	MSVM
Middle finger	0.992	0.992	0.999	0.996	0.993	0.993	0.246	4.177e-05	MSVM
Forefinger	0.993	0.993	0.999	0.994	0.993	0.993	0.371	3.48e-05	KNN
Middle finger	0.996	0.996	0.999	0.996	0.996	0.996	0.664	3.49e-05	KNN
Forefinger	0.996	0.996	0.999	0.996	0.994	0.996	5.239e+12	4.177e-05	RF
Middle finger	0.995	0.995	0.999	0.996	0.995	0.996	5.239e+12	4.157e-05	RF

Table 1 shows the proposed method without using NPE. As shown in the result suffering from the randomness and the process will not achieve higher accuracy. Whereas, Tables 2 and 3 shows the selection features from reduction features set close to 100 percentages, and achieve good result compare with other methods of a classification. The RF achieves the best result compared with other models when reduction features by NPE both RF and NPE have the same principles in splitting data. The proposed system compared with some studies on finger knuckle identification, Table 4 shows the summary of comparison for different techniques on the same dataset in terms of accuracy and equal error rate (EER).

The result in [39], [40] are implemented and listed in [4]. As show from the Table 4 the previous literatures are tested on 105 subjects for the forefinger only. The EER results show our method is more accurate from all the previous work. In the proposed method we doing two tested by 105 subjects to the forefinger as the literatures used and 190 subjects for all dataset subjects. The result shows all our methods are best EER value. The EER computed as the following equations.

$$EER = \frac{FAR+FRR}{2} \tag{5}$$

$$FAR = \frac{FP}{(FP+TN)} \tag{6}$$

$$FRR = \frac{FN}{(FN+TP)} \tag{7}$$

The FAR and FRR are computed for each class tested. The average of FAR and FRR are used to compute the EER value of overall the system. As shown in, the accuracy of middle finger and forefinger usning RF method achieved higher result than other techniques.

Table 4. Compartive result

Method	Number of subjects	Forefinger EER%	MiddleFinger EER%	Forefinger Accuracy	MiddleFinger Accuracy
DoN [39]	105	10.2	-	-	-
Fast_RLOC [40]	105	10.5	-	-	-
FastCompCode [40]	105	11.6	-	-	-
[4]	105	9.6	-	-	-
Our-MSVM	105	0.0116	0.024	0.977	0.951
Our-RF	105	0	0.026	1	0.946
Our-KNN	105	0.086	0.068	0.829	0.864
Our-MSVM	190	0.0049	0.0022	0.992	0.992
Our-RF	190	0	0	0.996	0.996
Our-KNN	190	0.018	0.015	0.993	0.994

4. CONCLUSION AND FUTURE WORK

The goal of this research is to develop a system for automated FKP identification. For feature extraction and dimension reduction, LDP and NPE are used. The study uses MSVM, RF, KNN classification algorithms with features derived from LDP and NPE to investigate image processing using machine learning methods that assure high efficiency and accuracy. The conclusion is that LDP combined with the NPE and RF classification method produces excellent results (accuracy, precision, and f-measure). When the number of training pictures is increased, the results show an increase in the (rates of recognition). In the future, we plan to suggest and improve the feature extraction method and another dimension reduction method.

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BIOGRAPHIES OF AUTHOR

Ali Mohsin Aljuboori received the BSc. and MSc in a computer science from AlNahrain University-Iraq in 2002, 2005 respectively. And the PhD from school of computer science and technology- Harbin Institute of Technology- China in 2014. Currently He is Editor-in-Chief of the AlQadisiyah Journal of Computer Science and Mathematics, and a Professor of Computer Science Department. His research interests include computer vision, machine learning, biometric. He can be contacted at email: ali.mohsin@qu.edu.iq.

Mohammed Hamzah Abed received the B.Sc degree in Computer Science from the University of Al-Qadisiyah, Iraq 2008, M.Sc degree in Computer Science from B.A.M. University, India 2011.Currently he works as an Assistant Professor at the Department of Computer Science, University of Al-Qadisiyah. And he is researcher at Budapest University of Technology and Economics (BME) His main research is in medical image processing, Speech recognition and machine learning. His current work is medical image analysis based on deep learning. He can be contacted at email: mohammed.abed@qu.edu.iq.