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HUMAN IDENTIFICATION SYSTEM BASED ON BRAINPRINT USING MACHINE LEARNING ALGORITHMS

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Abstract: In the medical field, due to the development of neuroimaging, several new methods of the biometric field have been attending and favorable candidates for the identification of people. These methods are part of "covert biometrics" that involve the use of measures of clinical and medical images to identify them. The prime motivation to use an invisible (Hidden biometric) is the fact that attacks of a system can be very hard to deal with. This privacy strongly contributes to the increased strongest in the topic of person's verification and identification. In this article, he extracted a brain signature, called a "brain fingerprint" from brain (MRI) Magnetic Resonance Image, obtained from 30 healthy subjects as images (1739), these real data sets from Yarmok Medical Hospital. These brainprint in this work are considered to be a hallmark of the brain. The objective of this proposed work which is design a robust, accurate human identification using human brain print, the brain classification based on several phases, included Data acquisition, Feature extraction processing depend on linear discrimination analysis (LDA) to gain important and interesting features of every image calculated by (number of features in the class). The proposed system shows rise detection precision with the features extracted based on LDA with automatical classifier learning by K nearest neighbor (K-NN) and logistic regression (LR) from the LDA method gained with the LR algorithm of (93%) while LDA method gained (91%) with K-NN.

Keywords: *Biometrics; Hidden biometrics; MRI, Brainprint; LDA; LR; K-NN.*

1. Introduction

Human identification and verification are increasingly being used in a variety of fields and applications, depending on the security level necessary [1]. Fingerprints are one of the most used biometric procedures [2], palmprint [3], iris recognition, and face recognition [4, 5]. These popular technologies are widely integrated into many devices with the system, they're useful, but they're also vulnerable to assaults. Biometric sets have shown to be useful in offering comprehensive identity theft protection solutions in this setting. Here are a few examples of typical plagiarism fears: Fake fingerprints have been linked to this in a number of papers [6]. Other attack techniques include iris and 2D/3D face recognition, as well as palmprint recognition (with vein biometry by near infra-red). A new sort of biometric has just been studied. They're called hidden biometrics, and their goal is to execute identification and verification processes utilizing features extracted from biometrics like the human brain that aren't visible to the naked eye [7]. In this

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situation, invisible biometrics may need the employment of certain technologies and software often employed in the medical industry and medicine. Passwords, PINs, and RF cards are common ways of human identity that are readily forgotten, stolen, or lost. Biometrics, which refers to the practice of identifying people based on their unique biological characteristics, are more acceptable approaches. Fingerprints, speech, face features, iris, and signatures are the most common bases for recognition in current technologies. Invisible biometrics, such as EEG (Electroencephalogram) [8], ECG (Electrocardiogram) [9], X-ray picture and MR image [10], might include crucial data. In this article, we explore person brain images obtained by magnetic resonance imaging. Because of its resistance to falsification, the brain magnetic resonance MRI signal can be employed as a viable biometric. They can be utilized for remote healthcare services as well as biometric recognition [1].

The goal is to create a one-of-a-kind brain print from each 3-D brain scan, which may subsequently be used to identify or verify persons. Some of the information around the folds, as well as cortical and subcortical structures, may be seen in these photographs. Because of numerous public biometric techniques, the proposed solution has the significant benefit of making identity theft/attacks a tough process to consider. "No one has the ability to change the traits of his brain."

The convolutions and the sulcus, which are called sulcus (**Sulco Geral patterns**), constitute the imprint of a person's brain. The growth and formation of the brain inside the skull provide a unique signature that differs from one person to another. In this context, several theories have addressed the question of the origin of brain folds [10]. The reasons are categorized into two types:

1. The first theory confirms that only outer mechanistic powers shape brain folds. In fact, the brain expands as a flexible part inside the skull and is a hard and fixed organ. The mechanical stresses results allow for sulco-gyral patterns to bee firm, stable and unique.
2. The second theory suppose a relation between the final brain structure and the morphology, and on the other hand, its cyto-architectonic and practical structure, brain growing, and the experience human learn, all that let the cortex and subcortical patterns to improve in featured ways [11].

This indicates that the folds of the brain differ widely between individuals; in addition to that recent studies in genetics and neuroscience have shown that switching genes that prepare different similar tweaks may also affect the shape and folds of the brain [12]. These studies show that the morphology of the person brain is unique. In addition, studies measuring the shape of the brain showed that the brain is asymmetric and that there are furrows (large sulcus) with a certain number in all individuals that differ in terms of shape, location and number of components. In fact, the same groove for all individuals can be somewhat deep, the length is less or more, somewhat curvy, and it can be fractured and composed of several distinct grooves [13]. Although the left and right hemispheres of the brain are highly identical in terms of shape, size, and weight. The brain tissue distribution for white and gray matter and the pattern of the folds differs in both halves. Therefore, the two brain hemispheres of the same person are not alike, and thus, the two brains of two different individuals will never be alike even in identical twins [14, 15, and 16]. Therefore, the folds of the brain as well as the

Sulcu Geral patterns are unique and specific to each person, and from an anatomical point of view this makes person brains different as well. Therefore, the main question that arises in this work is: Could these brain folds be used as biometric features? of verification or identification procedures?

Chen and Hu [17], the author presented recurrent neural network to individual identification based on resting state fMRI data based on only a short portion of resting-state functional MRI data, and the effect of global signaling and differences in atlases on individuals' recognition. In addition, identify the features of the neural network that show the uniqueness of each individual. The results indicate that the proposed model is able to identify individuals based on neural traits while providing additional information regarding brain dynamics, model was able to achieve 90+% accuracy on validation and testing data with used gated recurrent unit (GRU)

Nandpuru et. al., in [18], to discriminate between normal and abnormal MRI images, a support vector machine (SVM) and (LR) are utilized. Grayscale features, texture features, and symmetry features were all retrieved. Principal component analysis (PCA) was used to reduce dimensions and classification was performed using a Supporting Vector Machine (SVM) to evaluate the classification performance, linear, square, kernels and Logistic Regression were used and their accuracy was demonstrated at 74%, 84%, and 76%, respectively.

Kalbkhani et. al., in [19], the brain MRI is classified using multi-cluster features and K-Nearest Neighbors. They employed a second two-dimensional digital wavelet transform for the extraction function (DWT). The identified features were categorized into natural diseases or seven other diseases using K-NN and achieved an accuracy of 89.75% with 41 features.

2. Proposed Methodology

Image capture, image pre-processing, feature extraction, and efficacy evaluation are the four processes of the system, each of which is explained below (classification), as shown in Figure 1.

1. Because of its there is no need for a radiative contrast medium because of the high resolution., structural brain MR images (T1&T2) are employed to acquire brain pictures.
2. The preprocessing phase is required by the processing system to transform RGB pictures to grayscale images. Because of the strong performance of the cumulative histogram equalization approach in histogram equalization, the resultant grey picture contrast will be increased. Standardize the size of the brain images (100x100) before beginning the feature extraction step.
3. This characterisation stage is accomplished by using LDA to extract features from MR pictures (T1&T2), which are then utilized to transform the MRI from two dimensions to one dimension features for all images in order to maintain just the most significant aspects of the brainprint.
4. Evaluation of efficacy: Extracted characteristics were put into a classifier that recognizes or classifies objects using a machine learning method. A classifier that compares test photographs to images stored in a database might also be produced using an ML classifier.

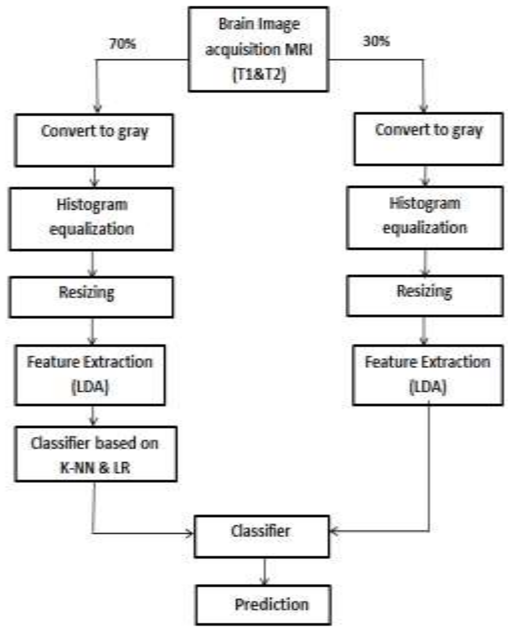

Figure1. Brain Recognition Proposed Methodology Process

2.1. Image Acquisition

In this work that magnetic resonance imaging was chosen. The data set for person identification based on brain scans is made up of (1739) MRI brain images of thirty people, including males and women. The brain imaging collection will also be subjected to many alterations before being used in the proposed identification method. These people are from the Medical Yarmok Hospital's database. 70 percent of the training datasets are made up of brain pictures. But the test took the data 30% from the dataset and (200) MRI for an unknown persons.

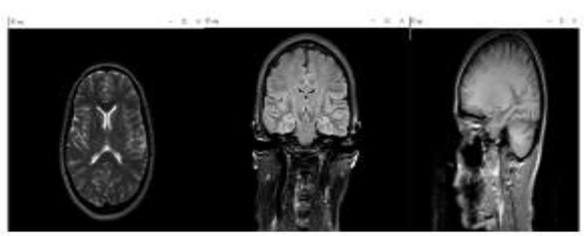

Figure 2. Sample contrast MRI shows images in three orientations, (A) axial, (B) coronal, (C) Sagittal.

2.2. Preprocessing:

This phase involves converting the MRI to grayscale using equation (1), figure (3), and then applying histogram equalization and scaling to 100*100 before proceeding to feature extraction. [21]

$$G = 0.2999R + 0.5870G + 0.1140B \qquad (1)$$

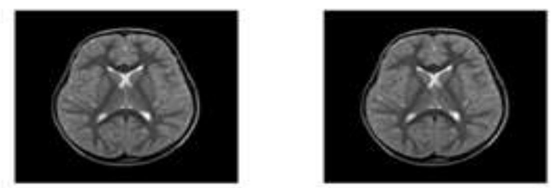

Figure 3. a- MRI sample image b-grayscale MRI

Histogram equalization is performed by spreading out the most common intensity values in an inefficient manner [22]. In computing histogram equalization, the cumulative distribution functions of the histogram are crucial as shown in the equation (2), (3) and (4).

$$H[i] = \sum_{x=1}^{N} \sum_{y=1}^{M} \begin{cases} 1, & if\ f[x,y] = i \\ 0, & otherwise \end{cases} \qquad (2)$$

$$\text{CDF[j]} = \sum_{i=1}^{j} H[i] \qquad (3)$$

f[x,y] : indicate the value of gray

H: illustrate the image's histogram.

CDF: cumulative distribution function

$$G[x,y] = \frac{CDF\ [f[x,y]] - CDF_{min}}{(N*M) - CDF_{min}} * (L-1) \qquad (4)$$

G[x,y] is a matrix for new enhanced intensity image.$CDF(X)_{min}$: is the cumulative distribution function's minimal value.

$N * M$: Number of images in columns and rows. L: Gray levels used =256.

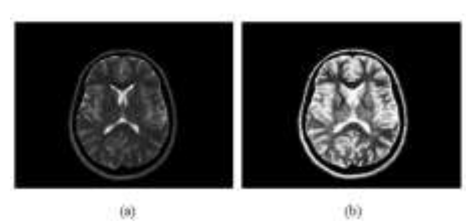

Figure 4. Histogram equalization (a) Grayscale Axial position capture. (b) Histogram Equalization result

2.3. Feature Extraction

Feature extraction includes decreasing the number of the resources that are needed for describing large data amounts. Also, feature extraction from certain data was one of the critical problems for effective applications related to machine learning. In the presented study, LDA was utilized as dimension reduction and feature extraction approaches from original brain images. LDA is producing feature vectors in the reduced dimensions.

2.3.1 Linear Discriminant Analysis (LDA)

LDA The technique of the dimensionality reduction process is to renovate the original features by reducing their dimensions and make the representation of data meaningful. The process of dimensionality reduction helps in picturing of high dimensional data and simplifies the classification for machine learning classifiers [23]. In addition, LDA looks for vectors in the underlying space that best distinguish between the classes. Furthermore, the LDA group's photos belong to the same class and are unique from other class images. There have been two measurements stated mathematically (between-class scatter matrix and within-class scatter matrix). The between-class scatter matrix SB and the in-class scatter matrix SW were specified as follows for each class sample:

Input: Given a data matrix N X M. Where N denotes number of samples X = (x1, x2, x3,.x_N). Each sample xi is represented as a vector with a length of M

Output: Creates a lower-dimensional shadow (fisher pictures) from a set of N photographs.

Steps:

1- N example photographs should be read. Each picture is represented by a row vector with M features, forming a data matrix X having N X M dimensions.

2- Partition the data matrix into c classes (ie x1, x2 … xc). Each class xj has M features. Find the mean of each class μj (1×M) using the equation

$$\mu_j = \frac{1}{n_j} \sum_{i=1}^{M} xi \quad (5)$$

3- Find the total mean of all data μ (1×M) using the equation

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i = \sum_{i=1}^{c} \frac{n_i}{N} \mu_i \quad (6)$$

4- Find the between-class variance (SB). Represents the difference between the mean and the samples of that class using the equation

$$S_B = \sum_{i=1}^{c} n_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (7)$$

5- Find the within-class variance SW. It represents the difference between the mean and the samples of that class using the equation

$$S_W = \sum_{j=1}^{c} \sum_{i=1}^{n_j} (x_{ij} - \mu_j)(x_{ij} - \mu_{j)})^T \quad (8)$$

6- Find the transformation matrix (W)

$$W = S_W^{-1} S_B \quad (9)$$

7- After that, the eigenvalues (λ) and eigenvectors (V) of W are computed.

Where the Eigen values are: λ= {λ1, λ2... λd}

And Eigen vectors are: V= { v1, v2, ..., vd}

8- Sorting the eigenvectors in order of their associated eigenvalues in decreasing order. The first k eigenvectors are then utilized to create Vk, which is a lower-dimensional space.

9- Using the equation, project all original samples (X) into LDA's lower-dimensional space.

$$Y = X\,Vk \quad (10)$$

Where each sample (Xi) that was represented as a point in an M-dimensional space will be projected onto the lower dimensional space to represent it in a k-dimensional environment. [24]

2.4. Classification Phase

The process of comparing the identity of input MRI feature vectors to the MRI vectors of people in the database is known as classification. LDA technique is to find out the method the vector of attributes proceeds for an instance number. Extracted features have been fed to the classifier. In supervised classification, K-NN and LR are used for classification.

2.4.1 K-NN Algorithm:

It is one of the popular instance-based learning methods in pattern recognition which is supervised by the learning algorithm. K-NN is a lazy learner since it does not have a training stage and performs well if all data are of the same size. The simplicity of the K-NN concept has made it a preferred classification tool for various applications. For example, to classify a Si sample, the algorithm first searches for its closest K neighbors in the feature space depending on the feature vectors and the specified distance. Then the algorithm executes the sounds of these neighbors according to their name. The object swatch will be categorized into the group containing the largest number of the same adjacent names. There are multiple distance metrics utilized in the K-Nearest Neighbor (K-NN) algorithm; the finest metrics are the Euclide an equation (11). [25].

$$\mathrm{D}(\mathrm{T},\mathrm{Y}) = \sqrt{\sum_{i=1}^{n}(T_i - Y_i)^2} \quad (11)$$

Where Y_i represents the feature and is known by an n-dimensional vector of features (a1, a2, a3…an), and the input vector T_i, i is the index vector in testing data, and D is Euclidean distance.

The steps of K-NN are summarized as:

a) The selection of 'k'.
b) Calculation of distance.
c) Sorting of distance in ascending order.
d) Finding 'k' class value.
e) Finding the dominant class.

Choosing an optimal "k" value is a difficult task, and a small value of "k" would not be suitable for accurately estimating population proportions around the test point. Choosing a higher value of "k" creates more bias and less probability variability.

2.4.2 Logistic regression (LR):

The first step in logistic regression classifier implementation is loading vectors of features for MRI brain dataset. The basic step in the LR algorithm is compute the probability of MRI brain features using the logistic function, and then select the maximum possibility of one of the 30 classes. Logistic Regression is used, MLR shares steps with binary logistic regression, and the only difference is the function for each step. In multinomial logistic regression, we have: Softmax function, Cross-entropy loss function, and stochastic gradient descent. [26]

1- In equation (12) Compute Linear Model.

$$Z_k = \sum_j W_{kj}\, X_k + b_k \quad (12)$$

X_1, X_2, X_3, …, X_k , set of features vectors of input X,W_1, W_2, W_3, …, W_k , set input number of weights, and Y_1, Y_2, Y_3, …, Y_{30} , classes result from output Y.

2- In equation (13) Calculate a multivariable generalization of the logistic function. $Y_k =$

$$Softmax(z_1, \ldots, z_k) = \frac{e^{zk}}{\sum_{k'} e^{z_{k'}}} \quad (13)$$

Where the inputs $z_k$are the logits.
Chose the maximumY_k.

3- In equation (14) Compute cross-entropy as the loss function.

Table 1. The experimental results of implemented LDA on the cropped brain images

Methods	Features length	No. of Features	Time of extraction
LDA	29	1739*29	5.00 s

$$L_{CE}\,(y,t) = -\sum_{k=1}^{k} t_k \log Y_k \qquad (14)$$

Where the log is applied element wise, t is a targets of range [0, 1].

3. Performance Measures

1. Precision:

reflects the total number of true positives divided by the total number of true positive instances and the total number of false positives By employing equations, white pictures or scanned images should be provided for the illustrations (15) [27]

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \qquad (15)$$

2. Recall:

Precision is the percentage of the data points this model claims were important in equation, and capacity represents the ability to locate every relevant example in a data collection (16). [29]

$$Recall = \frac{TP}{TP+FN} \qquad (16)$$

3. F-measure:

Equation (17) [29] shows the harmonic medium value of accuracy and recall, with F1 being the best at one and worst at zero.

$$F_1 = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \qquad (17)$$

TP: true positive, FN: False Negative, FP: False Positive

4. Result and Discussion

The goal of this research is to develop a system for automated brain recognition. The second component of this study, after preprocessing and scaling, is feature extraction using the LDA approach, with the input being a cropped brain picture and the output being image features.

Table (1) shows that LDA provides the bare minimum of characteristics, which is critical in recognition and identification systems.

The results of using both K-NN and LR machine learning algorithms for categorizing the characteristics produced from the previously stated feature extraction techniques, which include LDA as shown in table (2), are reported in the third part of the study.

Table 2. The experimental results of implemented the K- with LDA and LR with LDA

Method	Precision %	Recall %	f-measure %
LDA +K-	91%	82%	85%
LDA + LR	93%	77%	82%

Figure (5) and **(6)** show the comparison between the evaluations of performance rate of the classifiers for each class that are used in this paper for the prediction of human identification. The performance of the Logistic Regression is best. The best accuracy rate is 93% that got from the classification of techniques.

Table 3. Prediction results Comparison between Proposed work and previous works

Related Work	Classifier/ Tool	Accuracy (%)	Features Extraction method
Chen and Hu [17]	RNN	90+%	GRU
Nandpuru et. al., in[18]	SVM linear, square kernels and LR.	74%, 84% 76%	PCA
Kalbkhani et. al., in [19]	(K-NN)	89,75%	DWT
Current work	LR	93%	LDA
	K-NN	91%	

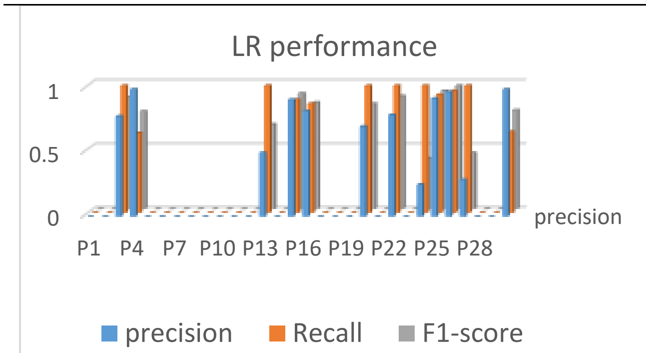

Figure 5. Logistic Regression performance

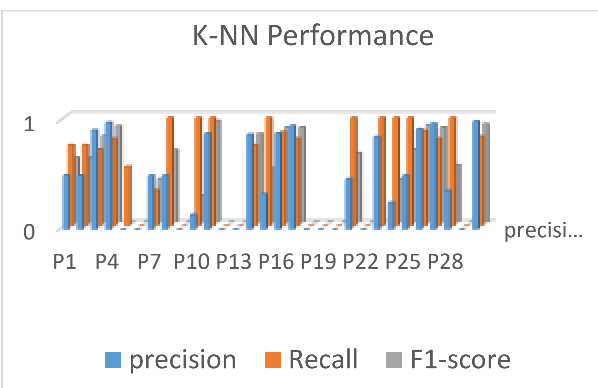

Figure 6. K-Nearest Neighbor performance

Comparing with the previous works referred to in up which relied on the algorithms of machine learning as classifiers for MRI of human's brain, it is important to indicate here that the works that will be referred to in this comparison were chosen depending on the type of similar to the datasets MRI of brain that have been classified, the maximum accuracy of previous studies for predicate tumor of brain in MRI dataset by machine learning techniques that used MRI brain dataset appears in Table (3), this table is also appearing to compare results between current work using LDA for feature extraction and previous works depending on feature extraction method applied with machine learning algorithms.

The suggested system processes are carried out on an HP laptop with a CORE i7 processor, 8 GB RAM, nVIDIA QUADRO graphics card, 500 GB hard drive, and Windows 10 64-bit operating system. The Python 3.6 software package was used to implement the proposed technique.

5. Conclusions

The LDA produces a superior result since it maintains its stability and only displays the most significant features; thus, when combined with ML, the LDA provides more precision and power in the recognition of human individuals. The LDA with K-NN gives a perfect result with an accuracy of 93 percent, and the LDA with the LR gives a perfect result with an accuracy of 93 percent, because the LDA gives the least number of features because it is considered the average feature extraction method (NO. of class-1), which means that it is unaffected by changes in the environment such as lighting and other factors. Two methods have been chosen, which are (LR and K-NN) from among the methods of machine learning, because the other methods, for gave a low accuracy rate compared to the above methods.

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Conflict of interest

The publication of this article does not cause any conflict of interest.

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