ABSTRACT

In the last decenniums, Counterfeiting and identity spoofing and have been noticed at a very high rate, it has become critical to develop a smart and developed biometric security system that is in sync with the advancement of information technology (IT) services. As a result, humans continue to conduct studies in the field of brain recognition. The fact that attacks on hidden biometric systems (such as brain fingerprints) are so difficult to succeed is the main motivation for using these biometrics. Biometric systems' privacy contributes greatly to improving the degree of robustness in terms of individual verification and identification. In this research, the convolutional neural network classifier, which is considered one of the most important classifiers of the deep education type, was relied on to classify data sets including 300 brain MRIs (Magnetic Resonance Imaging) into 30 classes. Note that the brain MRI scans are for the thirty patients, ten images to each patient, these patients real data base from Medical Yarmok Hospital. The classifier was combined with the linear discriminative analysis (LDA) the powerful feature extraction, extracting a brain signature, called “brainprint” from brain MRI images. The proposed algorithm is developed to classify brain by several stages including; data acquisition; preprocess; feature extraction using (LDA) to get important information of image. The proposed system show high accuracy with features extracted using Linear Discriminate Analysis with classifier CNN. The Experimental results getting after implementations and testing is of Precision 100%.

Keywords: MRI; Linear Discriminate Analysis; Feature Extraction; Classification; Convolution Neural Networks.

I. INTRODUCTION:

In these days the identification and verification of humans are growing applied in various areas and applications based on the security grade required [1]. Some of the more popular biometric methods include fingerprints, palm print, iris recognition, and face recognition [2], but unsafe to possible attacks. In this context, the biometric sets have been effective in providing robust identity theft prevention solutions. For example, some common fear of plagiarism: Many articles have fake fingerprints assigned to this [3]. Other can also be cited attack methods like recognition for iris and 2D / 3D face, and palmprint. Although numerous good have been proposed to ride this issue, Therefore, another method was considered to solve these problems. More recently, an emerging category of biometrics has been explored. They are called hidden biometrics. Its purpose is to perform identification and verification of the features used extracted from any part of the human body, which cannot be achieved or seen due to direct naked eyes. [4]. In this case, invisible biometric might need some particular devices and common software used in the medical field and medicine. For example, invisible biometric can contain important signals, like EEG (Electroencephalogram), ECG (Electrocardiogram), X-ray image and MR image [5], etc. In this article, Brain magnetic resonance imaging (MRI) plays an increasingly important role in biomedical research and the field of automated medical image analysis. As MRI has the ability to provide information about the structure of the brain, one of the most complicated organs in the human body is the brain, [6]. The goal is to extract a unique brain fingerprint from each 3-D image of the brain, to be applied for identification or verification. These images include some of the information around the folds, with structures of cortical and subcortical. Through several public biometric techniques, the suggested approach has the main benefit, making identity theft/attacks a hard process to think about. “No one can modify the features of his brain”.
Deep learning refers to a fairly broad class of machine learning technologies and structures that depend on learning multiple levels represented by creating a hierarchy of features extracted from inputs, where some lower levels can help in identifying input features for higher levels [7]. The DL architecture expands the traditional neural network by adding hidden layers to the neural network architecture between the input and output layer, to model nonlinear and more complex relationships depending on the network level. The concept of DL work has recently gained the attention of researchers in terms of good performance and accuracy in results, to become one of the best solutions for medical image analysis and processing applications and its assistance in segmentation, classification, and reduction of image distortion. With all this, the performance of neural networks in general remains and (SVM) is the most common and widely used method, and it performs well for many periods [8]. In recent years, deep architecture DL models have played an important and exciting role in representing complex relationships very efficiently without the need for a large number of nodes. Therefore, the importance of deep education has increased to become one of the most important modern technologies in various fields of health informatics such as medical and biological information and medical image analysis [9]. The contribution of this paper is applying the deep learning concept using CNN can reduce a lot of computation because it doesn’t need to visit the image pixel by pixel instead CNN uses filters to perform an automated brain identification using brain MRI images and measure its performance. The proposed methodology aims to differentiate between persons by using brain MRI images. The proposed methodology uses a set of features extracted by the linear discriminative analysis (LDA) feature extraction technique from the brain MRI images, to train the CNN classifier for brain classification to human identification. Generally, the steps used for achieving this were: brain acquisition, feature extraction, and lastly classification.

II. RELATED WORK

Polepaka, S. et al in 2019 used Interactive Diagnosis Support System (IDSS) method and indicated the drawbacks regarding non-illumination and the low contrast that is related to MRI image of brain tumor which impact the process of precise classification regarding the image. Therefore, IDSS has been utilized in 3 stages which are image pre-processing to enhance the no illuminated features, image classification and feature extraction that are achieved with the use of 2-phase interactive SVM Classification. Local binary patterns in feature extraction for precise classification regarding unusual and usual MR images of brain [10].

Milica M. Badža and et al. 2020: this method represents The structure of the CNN and its use in the classification of three types of brain tumors, the designed network is one of the simplest types of pre-trained networks, the MRI images of the T1 contrast were adopted. Two 10-fold validation and two database methods were used in assessing the network. 10-fold validation methods were used to test the network capacity and the concept of generalization, and then test optimization based on the basis of magnetic resonance imaging. Accuracy, using 10-fold validation, was approximately 96 percent [11]

Alejandro-Israel and Barranco-Gutiérrez 2020 The authors focus in their work on knowledge as a brain data by classifying magnetic resonance imaging images of the brains of bilingual people as the English language is their common language. The work in the neural network relied on testing the hidden layer until the number of neurons reached two in the hidden layer. The number of entries for the network is up to nine hundred, and the effectiveness of the classifier has been verified, which often works under the supervision of statisticians to show the color curves expressing the difference of each type [12]

R.C. Suganthe, and et al. 2020 use the RNN convolutional neural network to extract features that aid in classification algorithms to detect the tumor in magnetic resonance imaging of the brain. As the convolutional neural network helps in detecting the tumor in the early stages, it gave a classification accuracy of up to 90% [13]

III. METHODOLOGY

The system is divided into four stages, each of which is described below.: image acquisition, pre-processing image, feature extraction, and Evaluation of efficiency (classification) as explained in Figure1.

1. Brain image acquisition: Structural brain MR images (T1&T2) are used because of their high resolution and lack of the need for a radiative contrast medium.

2. Preprocessing step: it is necessary for the processing system for converting the RGB images to gray ones. Converting RGB colored image into gray-scaled image is affecting some features of images, after following
the inputted colored images conversion to the greyscale, the resulted grey image contrast will be improved through the use of the cumulative histogram equalization technique because of good performance that this technique has in histogram equalization and Standardize the size of the brain images (100x100) before entering the feature extraction stage.

3. Features extraction and Dimensionality reduction: this characterization step is achieved using Linear Discriminant Analysis (LDA) to extract features from MR image (T1&T2) and used in order to keep exclusively the most relevant characteristics of the brainprint convert the MRI from two dimensions to one dimension features for all images .

4. Evaluation of efficiency: Extracted features have been fed to a classifier that is recognize or classify via utilizing an algorithm of Deep Learning. Also, a classifier is comparing the test images with images saved in database might be achieved with CNN classifier

After creating the dataset using a MRI for 30 real persons each one has 10 images then the total is 300 MRI, which are divided into 30 classes, after that feature extraction by using LDA, then the classification using the CNN algorithm. Figure (1) shows the proposed methodology process.
1. Image acquisition

To get to know the brain, the first step is brain acquisition with the advancements in different neuroimaging technologies like MRI is considered to be of high spatial precision with high resolution fig(2), as it does not require a radioactive contrast media, and this makes it non-invasive. The data set that used in person identification depending on brain images composed of 300 colored brain images for both men and women. The dataset of brain images also will pass across multi changes in order to use it in the proposed identification system. The number of images is 300 images to thirty person, ten images to each one, with size (100x100). These persons real data base from Medical Yarmok Hospital. The datasets that is used of brain images 70% for the training and the 30% for test set of samples.

Figure 2: Sample contrast MRI images shows T2-weighted images in three orientations (A) Axial, (B) Coronal, and (C) Sagittal.

2. Preprocessing:

This step contains:

- convert the MRI to grayscale by using equation (1), fig (3).[14]

\[ G = 0.2999R + 0.5870G + 0.1140B \] ……….. 1

- Apply histogram equalization. Histogram equalization achieves through diffusing out the most values of frequent intensity in efficient manner [15]. histogram cumulative distribution function important in computing histogram equalization as shown in equation (2) and (3).

\[ Cdf(X) = \sum_{i=1}^{X} h(i) \] ……….. 2

Where X represent the gray value and h illustrate the image’s histogram.

\[ T[\text{pixel}] = \text{round} \left( \frac{\text{cdf}(X) - \text{cdf}(X)_{\text{min}}}{E*F - \text{cdf}(X)_{\text{min}}} \right) * (L - 1) \] …..3

\( \text{cdf}(X)_{\text{min}} \): is the minimum value of the cumulative distribution function.

E * F: Columns and rows number of images

L: Gray levels used =256.

- And resizing to 100*100 before inter to the feature extraction.

Figure 3: grayscale MR image
3. Linear Discriminant Analysis (LDA)

LDA has been referred to as the fisher-face approach also, which is utilized for overcoming the limitations of PCA in terms of its application that has been kept in a small image data-base. It was accomplished via the projection of an image onto eigenfaces space through PCA, then implement pure LDA over it for classifying eigenface space projected data [16]. Besides, LDA is searching for vectors in underlying space that are best discriminating between the classes. Furthermore, the images of the LDA group are related to the same class and separate distinctive class images. Mathematically, there have been 2 measures specified (between-class scatter matrix and within-class scatter matrix) [17]. For every class sample, the between-class scatter matrix $S_B$ and in-class scatter matrix $S_W$ were specified as follows, and we see in equations [5]:

- d-dimensional mean vectors are computed for various classes from the data-set.
- Computing scatters matrices (within class scatter and in-between-class matrix)
- Computing the eigenvectors ($e_1, e_2, ..., e_d$) as well as corresponding eigenvalues ($\lambda_1, \lambda_2, ..., \lambda_d$) With regard to scatter matrices.
- Eigenvectors are sorted via reducing the eigenvalues as well as choosing $k$ eigenvectors with maximum eigenvalues for creating $(d \times k)$ dimensional matrix $W$ (in which each one of the columns is representing eigenvector).
- Using such $(d \times k)$ eigenvector matrix for transforming the samples on a new subspace, this might be summarized via matrix multiplication: $Y=XW$ (in which $X$ indicates $n \times d$-dimensional matrix representing $n$ samples, and $y$ indicates $n \times k$-dimensional samples in a new subspace).

\[
\begin{align*}
\mu_j &= \frac{1}{n_j} \sum_{x_i \in \omega_j} x_i \\
\mu &= \frac{1}{N} \sum_{i=1}^{N} x_i = \sum_{i=1}^{c} \frac{n_i}{N} \mu_i \\
S_B &= \sum_{i=1}^{c} n_i(\mu_i - \mu)(\mu_i - \mu)^T \\
S_W &= \sum_{j=1}^{c} \sum_{i=1}^{n_j} (x_{ij} - \mu_j)(x_{ij} - \mu_j)^T \\
\end{align*}
\]
In which: $X_{in}$ representing $i$th sample in $j$th class.

$$W = S_W^{-1}S_B$$

$$W \nu = \lambda \nu$$

$$Y = XV_k$$

In which:

- $N$ representing the total number of samples.
- $n_i$ representing the number of samples related to the $i$th class.
- $\mu_i$ representing the projection of the mean of the $i$th.
- $\mu$ representing the projection of total mean regarding all classes
- $S_B$ between class variance
- $S_{W_i}$ representing the within-class variance of $i$th class, and differences between the mean
- $X$ representing the input sample, $\nu = $ Eigenvector, and $\lambda =$Eigen value, $X$ is a $n*d$-dimensional matrix for $n$ sample, $Y$ is transform of $n * k$-dimensional in new subspace

IV. CLASSIFICATION:

The extracted features are fed to the classifier. For classification, one of the major deep learning classification methods is utilized, which is CNN. Deep learning algorithms are considered perfect in classification and give an accurate result with a high score especially when dealing with big datasets. Any classifier in deep learning techniques has a set of layers. CNN is working in the same way if they have 1, 2, or 3 dimensions [18], while the difference is considered as the input data structure and how a filter, also referred to as feature detector or convolution kernel is moving across data. The attained CNN layers and their parameters in this work is a 1dimensional and it consists of 1D convolution layer, MaxPooling layer, Dense layer , flatten layer, and Activation function (Leaky ReLU) except the last convolution layer we used linear activation function. The proposed CNN model is shown in figure (4) that will define the layers of it which is 23 layers:

1. 8 convolutional layers for feature extraction of type of 1D.
2. 6 Maxpooling 1D layers
3. 7 LeakyRelu.
4. One fully connected layer is represented by the (Dense).
5. One flattens layer.
V. PERFORMANCE MEASURES

1. Precision: represents the amount of the true positives that are separated by the number of the true positive cases as well as the number of the false positives. White photographs or scanned images should be supplied for the illustrations, by using equation (6)

\[ \text{Precision} = \frac{TP}{TP + FP} \] …………6

2. Recall: The capability of finding every relevant example in a data-set, precision represents the ratio of the data points this model states was relevant in equation (7).

\[ \text{Recall} = \frac{TP}{TP + FN} \] …………7

F-measure: The harmonic medium value of accuracy and recall, with F1 being the optimal value at one and worse at zero, equation (8)

\[ F_1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \] …………8

VI. RESULT AND DISCUSSION

This study aims to implement a system for automatic brain recognition. After performing the preprocessing (resizing and histogram equalization) in table(1), the third part of this work is feature extraction using the method LDA, the input of this part is cropped brain image and the output is image features, LDA gives a minimum amount of features and this is an important point in recognition and identification systems in table(2). In the fourth part of the work, a description is obtained about the results of applying CNN algorithm for classifying the features obtained from the previously described feature extraction algorithms which include LDA. The experimental results of implemented classification algorithms CNN with LDA are shown in tables (3)

| Table (1): The experimental results of implemented Preprocessing step |
|-----------------|-----------------|-----------------|
| Methods         | Input           | Output          |
| Resize          | 300 image (640x480) | 300 image 100x100 |
| Histogram equalization | 300 image (100x100) | 300 image 100x100 |
The proposed system procedures are accomplished on a hp laptop with CORE i7 , 8 GB RAM size, the screen card is nVIDIA QUADRO, 500 GB HDD, and the operating system is windows 10 , 64 bit. The proposed methodology was performed using the Python version 3.6 software package.

VII. CONCLUSION

We developed a new method for extracting a robust biometric signature (i.e. brainprint) from MR brain images as a result of this study. As we saw, the brainprint is computed by converting curvilinear slices (which include the cerebral cortex) into 2D images. Feature extraction was achieved through The LDA. It gives a better result because it still retains its stability and gives only the important features, so the LDA when used with CNN gives more accuracy and power in recognition of human beings. The LDA with the CNN gives a perfect result with an accuracy of 100% because the LDA gives the minimum number of features due to, it is considered as the average feature extraction method, which means that even if the environment is changed such as lighting and other factors it does not affect.

REFERENCES


Table (2): The experimental results of implemented LDA on the cropped brain images

<table>
<thead>
<tr>
<th>Methods</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDA</td>
<td>300image(100x100)</td>
<td>1739</td>
</tr>
</tbody>
</table>

Table (3): The experimental results of implemented CNN algorithm with LDA

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Precision %</th>
<th>Recall %</th>
<th>f-measure %</th>
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<tbody>
<tr>
<td>LDA+ CNN</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
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