JOURNAL LA MULTIAPP

VOL. 03, ISSUE 04 (198-206), 2022
DOI: 10.37899/journallamultiapp.v3i4.692

Human Identification Model Considering Biometrics Features

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Article Info

Article history:
Received 12 July 2022
Received in revised form 12 August 2022
Accepted 15 August 2022

Keywords:
Feature Extraction
Classification
Hidden Biometrics
MRI
Brain Print
LDA

Abstract

In the medical field, brain classification is an effective technique for identifying a person through his brain print based on the hidden biometrics of high specificity included in the magnetic resonance images(MRI) of the brain, as this privacy strongly contributes to the issue of verification and identification of the person. In this paper, the brain print is extracted from the MRI obtained from 50 healthy people, which were passed through several pre-processing techniques in order to be used in the classification stage through convolutional neural network model, among those pre-classification stages, data collection after extracting the influential features for each image, which was based on linear discrimination analysis (LDA). The experimental results showed the importance of using LDA for feature extraction and adoption as input for K-NN and CNN classifiers. The classifiers proved successful in the classification if the features extracted with the help of LDA were adopted. Where CNN had the ability to classify with an accuracy of 99%, 82% for K-NN. The final stage in identifying a person through a brain fingerprint relied mainly on the model's success in classifying and predicting the remaining data in the testing stage.

Introduction

With the increase of critical systems and applications, the need to know and verify people is required to obtain a high level of security (Naït-Ali & Fournier, 2012; Cament et al., 2014). Authentication and identification of a person or an individual is an important requirement in numerous governmental and civilian applications where errors in recognizing a person can be costl (Alazawi et al., 2019). Biometrics is the skill of establishing or determining an identity based on the physiological or behavioral attributes of an individual. The biometric features are both physical and biological; thus, the features include fingerprints, face recognition, iris recognition, signature, hand geometry, voice recognition, which are all physical characteristics, while gait, keystroke, etc. are biological characteristics (Heble & Nikhare, 2017).

Biometric techniques are of great importance in achieving security in verification operations through fingerprints, handprints, facial recognition, eye recognition (Hadid et al., 2015; Fayaz et al., 2016). Biometrics are used to identify individuals based on their physical and behavioral characteristics. Such as biometrics such as fingerprints, hand and face geometry, iris, etc (Obaidat et al., 2019).

Biometric techniques have been widely used in many important systems and applications, in terms of their usefulness in identifying people, although these measurements are unique to each person who has potential threats through security attacks (Kim & Pan, 2017). Hence the need to find biometric features that are difficult to falsify, for example, magnetic resonance images (magnetic resonance brain print). The difference in rest or relaxation times led to tissue variability, which is the best option among all available imaging methods (Ayadi et al., 2018; Raja, 2019). Many studies and researches consider biometric features of brain fingerprints, the most common of them are discuss.

Aloui et al. (2018), the authors proposed extracting brain fingerprints based on cortical regions shown in MRI images of the brains of more than 200 people. These images were processed by 3D processing of cortical surfaces and converted into 2D maps, where the features were extracted using Wavelet Gabor Transform. Regarding the performance of the proposed model, it obtained an accuracy of 99.6%

While Chen & Hu (2018), presented a neural network-based model to classify people using a short piece of data from the brain in MRI images in terms of individual status, influence of signals, and differences in brain maps. The results indicate that the proposed model succeeded in identifying individuals based on neurological features if additional information regarding brain dynamics was provided.

Ayalapogu, R. et al. In (2018), the authors proposed a diagnostic model based on advanced computer techniques, which classifies brain images through MRI analysis. By applying statistical features associated with dual-tree M-band transformation (DTMBWT). Maximum Margin Classifier, SVMs. The results indicated to the researchers that the proposed model will provide good results with respect to molecular brain tumors (REMBRANDT) with a classification accuracy of 97%.

The extraction of brain MRI features is one of the most important operations required by the proposed system, as LDA was adopted to extract these features and then use them to classify people through the convolutional neural network. Through preprocessing, features can be supported to get the best possible results, such as image conversion to grayscale, histogram equalization, and input image size control. In this paper, identification of the human brain is done using magnetic resonance images, trait extraction using LDA, and a CNN classifier. The steps used to achieve the goal of the system are data set creation, brain acquisition, preprocessing, feature extraction, and the final stage is classification.

Pre-processing

In this article, in order to obtain the best results by either feature extraction or classification stages, it is important to process the brain imprint in the MRI images. The preprocessing operations are apply using basic image processing techniques such as grayscale conversion, histogram equalization, and image resizing.

Grayscale image: Convert brain print image to grayscale image. Histogram equalization: The graph equation is achieved by spreading most of the repeated density values in an inefficient mode (Rajinikanth et al., 2020; Sun et al., 2015).

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

Where, f[x,y] is appear the gray value, and H is a histogram of the image. Resizing: resize Brinprint MRI to 100*100, resize image is an important operation to enable the ML algorithms and CNN model to work with standardized scales before starting to classify the pre-assembled images from the third pre-processing phase (Rajinikanth et al., 2020; Vasuki et al., 2017).

Feature Extraction

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 high dimensional data and simplifies the classification for machine learning classifiers, LDA has been known to search the core space for vectors to include better attributes between classes (Santhi et al., 2018). LDA has been known to search the core space for vectors to include better attributes between classes. In addition, LDA associates images of the same class with common attributes and images with separate attributes (Tharwat et al., 2017).

LDA for Feature Extraction Algorithm

Input : Image matrix, X = (x_1, x_2, x_3, …, x_n). where x_{i-n} is a vector with m attributes.

Output : An image with fewer dimensions, with effective features

Step1 : Divide the data array into c classes (x1, x2... xc).

$$\mu_j = \frac{1}{n_j}\sum_{i=1}^{M} xi \qquad \dots\dots\dots\dots (2)$$

Step2 : Compute mean of all data μ (1×m) by equation

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i = \sum_{i=1}^{c}\frac{n_i}{N}\mu_i \qquad \dots\dots\dots (3)$$

Step3 : Compute the variance between classes by the equation

$$S_B = \sum_{i=1}^{c} n_i(\mu_i - \mu)(\mu_i - \mu)^T \qquad \dots\dots\dots (4)$$

Step4 : Compute the variance within class by the equation

$$S_W = \sum_{j=1}^{c}\sum_{i=1}^{n_j}(x_{ij} - \mu_j)(x_{ij} - \mu_{j)})^T \quad \dots\dots\dots..(5)$$

Step5 : Compute transformation matrix (W)

$$W = S_W^{-1}S_B \qquad \dots\dots..(6)$$

Step6 : calculate eigenvalues (λ) and eigenvectors (V) of W

$$W\ v = \lambda v \qquad \dots\dots.(7)$$

Step7 : Sorting the eigenvectors, where a first k eigenvector as a lower dimensional V_k

Step8 : The new image is the result of projecting the original X samples to lower dimensions

$$Y = X\ Vk \quad \dots\dots..(8)$$

Classification Models

In the field of biometric prediction, machine learning and deep learning algorithms are the best choices, in this work KNN was used as machine learning and CNN as deep learning algorithm. All deep learning and machine learning algorithms are subject to performance evaluation using confusion matrix and its related set of metrics.

Conventional neural network (CNN)

The classifier relies for its input on feature extraction. Since the deep learning algorithms succeeded in classifying the images, CNN was adopted in the classification stage. Deep learning algorithms give accurate results especially when dealing with input images represented by large or huge datasets. A CNN works in the same way, whether it has a 1D or 2D. A CNN consists of a number of layers that include active functions that process the input data (Wu, 2017; Oh et al., 2020). The difference of any model in deep learning depends on the structure of the input, the number of layers, and the movement of the filter, which is also called a feature detector or kernel (Oh et al., 2020).

K-NN

The K-NN classifier does not have a training phase like CNN, but it performs well if the input data is of the same size. The K-NN algorithm searches for the nearest neighbors of the selected point K within the features depending on the given distance and the vectors of those features. For distance measurement, the best choice is the Euclidean equation (Oh et al., 2020).

Proposed System

The proposed system includes three main stages, first: pre-processing, which includes converting images to grayscale and standardizing images size in proportion to the input of the classifier, second: extracting features for images after the pre-processing phase using LDA technology, classifying inputs (brain images) and evaluating The performance of the classifier in order to determine its efficiency.

CNN layers with their parameters in this work are consist of convolution layer, MaxPooling layer, flatten layer, and activation functions: (ReLU) and linear. The architecture of the proposed CNN model for classifying human brain fingerprint consist of six convolutional layers, four Maxpooling layers, fully connected layer, and flatten layer.

The identification proposed system was explained in Fig. (1), this stage comes after conducting an evaluation of the performance of each of the previous classifiers, as the results of evaluating the performance of the CNN classifier showed the superiority over K-NN. Therefore, the CNN model is adopted in classification processes and brainprint identification based on features and data previously stored in the database after each process of extracting features by LDA. The decision to recognized a brain print or not depends on the comparison between the features of the stored class and the new inputs (to be recognized and identified).

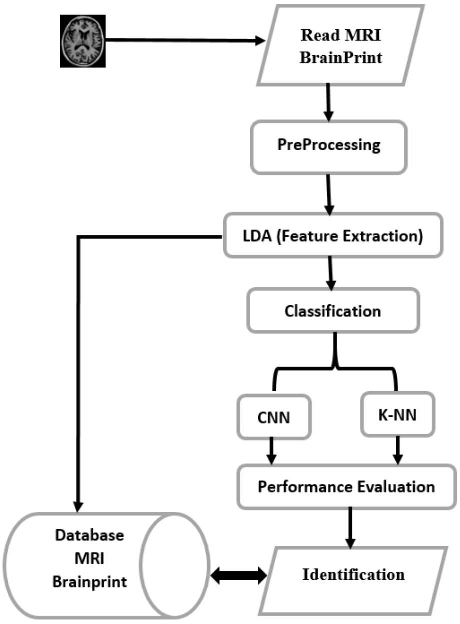
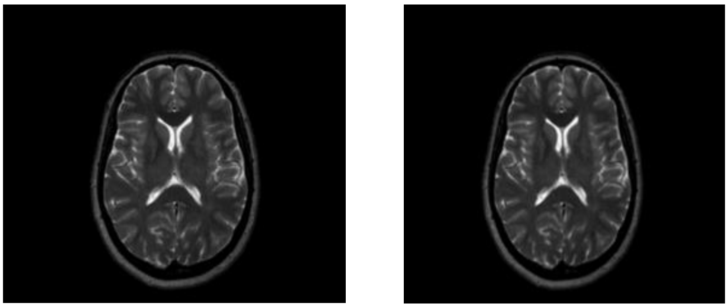


Figure 1. Human Identification from MRI Brainprint

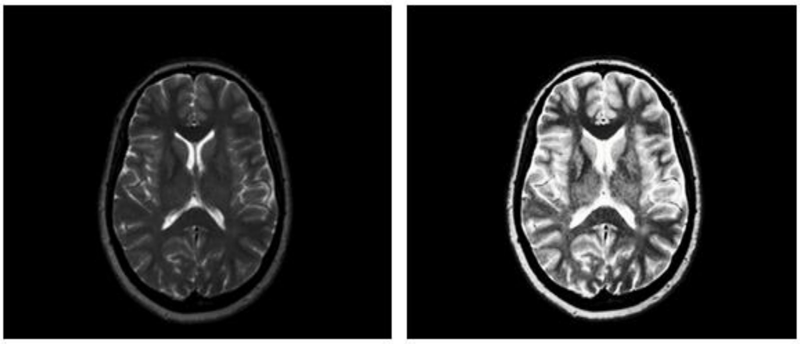
Experimental Results

Using LDA, features of approximately 50 brainprints were extracted and stored in the proposed system's database. In the classification phase experiment, the CNN classifier is trained on 30 (out of 50), the rest will be used in the testing phase and brainprint recognition. This step contains the convert the MRI to grayscale, Fig. (2) is shows the result of Gray level convert for Person, then apply histogram equalization on the gray image is shown in Fig. (3), finally, the result image is resizing to 100*100 as shown in Fig. (4) before inter to the feature extraction



(a) (b)

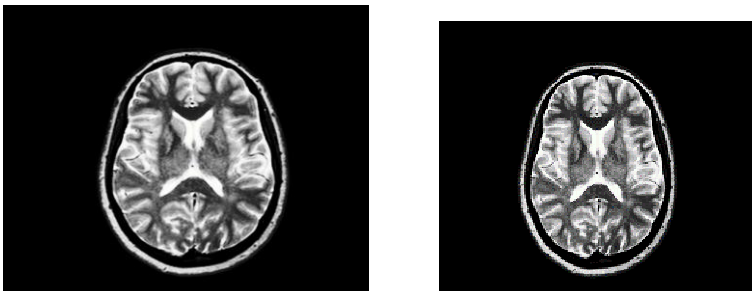
Figure 2. Grayscale Conversion: (a) Origin Brain MRI, (b) Grayscale Image.



(a) (b)

Figure (3). histogram equalization, (a) Grayscale, (b) Histogram Equalization result

Resize image is an important operation to enable the ML algorithms and CNN model to work with standardized scales before starting to classify the pre-assembled images from the third pre-processing phase. The resize resulting image is shown in Fig. (4).



(a) (b)

Figure 4. The resize of MRI, (a) Histogram Equalization, (b) Resize 100x100

Performance Evaluation of CNN Model

Three comparisons have been made among main performance metrics precision, recall, and F-measure, which have been used in the system. All Precision metrics for LDA with CNN model are shown in Fig. (5)

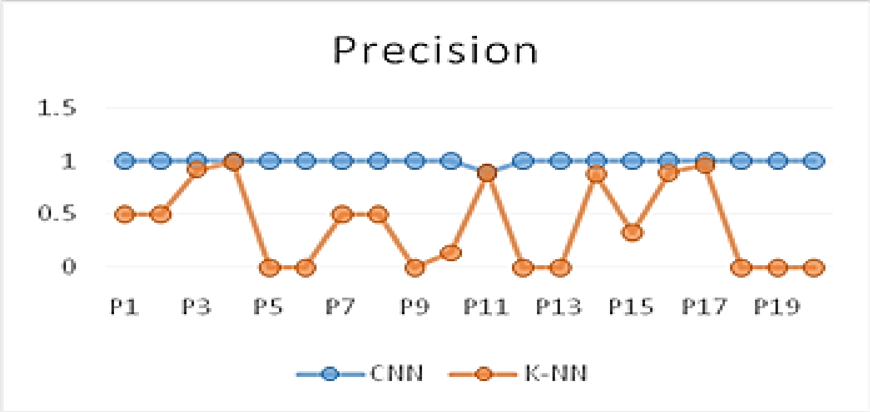


Figure 5. Precision for K-NN and CNN

All Recall metrics for LDA with CNN model are shown in Fig. (6).

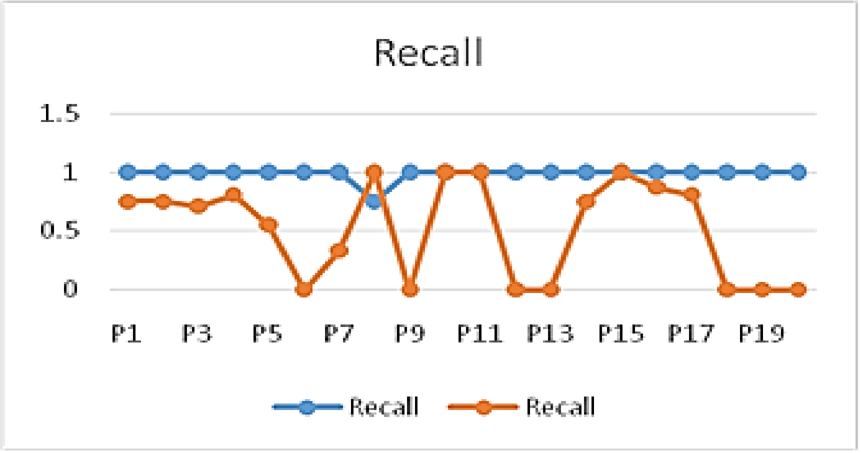


Figure 6. Recall for K-NN and CNN

All F1-score metrics for LDA with CNN model are shown in Fig. (7).

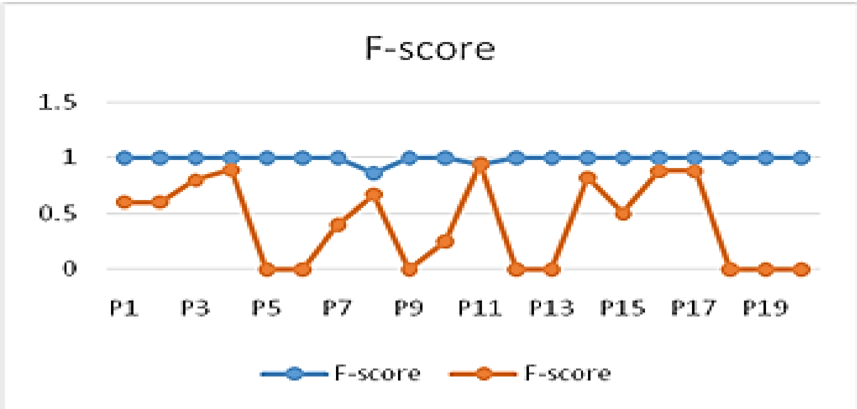


Figure 7. F-score for K-NN and CNN

The purpose of classification is to predict the closest to the classes within the data sets, therefore, the performance evaluation of any classifier had the main role in choosing the best model for such a task.

A selected model will be used in the stage of identifying the person based on magnetic resonance images of the brain. Table (1) contains the weighted average of the Precision, recall, F scores, and accuracy for LDA with models (K-NN and CNN).

Table 1. Weighted average for CNN and K-NN

Model	Weighted avg.			Accuracy
	precision	Recall	F1-score	
K-NN	91%	82%	85%	82%
CNN	100%	99%	98%	99%

Figure (8) shows that the highest accuracy belongs to CNN, which is close to 99%, while the accuracy of K-NN reaches 82%, for this reason CNN was chosen as a final classifier in the two stages of classification and identification of a person through a brain fingerprint

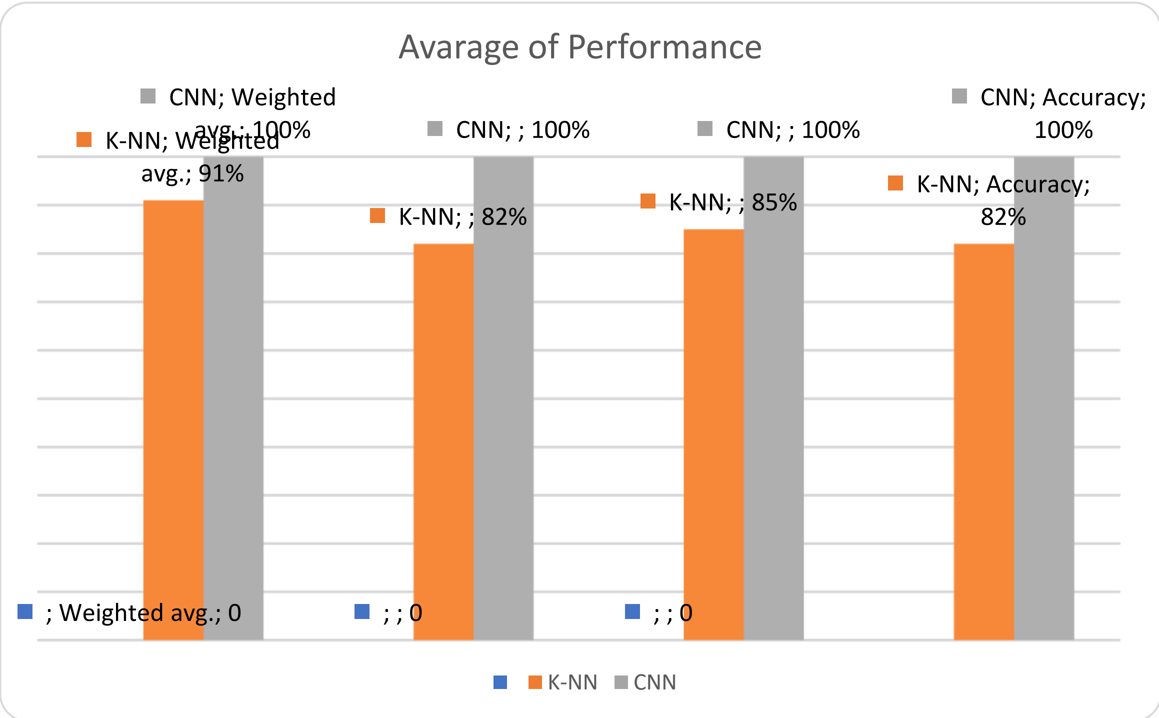


Figure 8. Accuracy average for K-NN and CNN

Conclusion

LDA still retains its ability to give the best results in feature extraction, so it was the best choice to combine it in this work with CNN to obtain high-resolution classification results. The CNN architecture had a key role with the activation functions in achieving high accuracy in classification stage, then using it in the stage of identifying the person by his brain fingerprint. It is important to note that LDA with CNN remains effective even if the environment changes in terms of lighting and other factors.

Acknowledgment

The Authors would like to thank Mustansiriyah University (https://uomustansiriyah.edu.iq/) Baghdad -Iraq for its support in the present work.

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