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Neural networks based face recognition system for biometric security

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ABSTRACT

Students' frequent attendance in class is crucial for performance evaluation and quality control in the current educational system. Calling names or signing documents are the traditional procedures used in the majority of institutions, both of which are time-consuming and unsafe. The automatic attendance management system is discussed in this article for convenience or data accuracy. However, in real time system fast and reliable face recognition systems are needed with fair amount of accuracy. This research describes a neural network-based principal component analysis facial recognition technique. The proposed approach uses inverse PCA for feature extraction and artificial neural networks for reconstruction to increase accuracy. The suggested methodology's key benefits are its greater accuracy (97%) and rapid processing.

Keywords: Face recognition, PCA, ANN

1. INTRODUCTION

Evaluating attendance is among the most fundamental criteria for determining the effectiveness of student participation in educational organizations (Bouridane, 2009). Measuring student attendance has grown to be a significant concern for schools. Manual process documenting attendance requires a large amount of energy and time (Baron, 1981). The conventional manual method of taking attendance involves shouting out students' names or taking attendance without using an attendance sheet. These methods take a lot of time and can leave room for fraud (Zhao et al., 2003). The aforementioned issues might be resolved by developing an automatic attendance system (Turk and Pentland, 1991). The easiest way to capture attendance is biometrics. Fingerprint based systems are complex and time consuming. Therefore, human face can be used, for the attendance monitoring. In Figure 1, face based automatic attendance system is shown. First of all, image is captured which is a part of video frame. From the captured image face is detected. Next face recognition is performed by matching with faces database and if face is identified attendance is recorded and attendance database is updated.

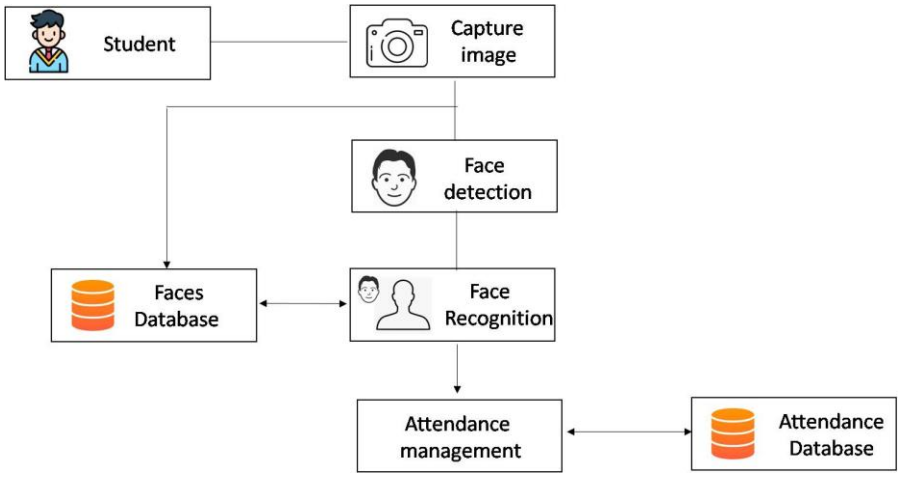

Figure 1 Schematic of face based automatic attendance system

The human face is a complex, multi-dimensional structure that can communicate a lot of data about the person, comprising facial characteristics, emotion and feelings. It is a difficult task that takes a considerable amount of time and effort to analyse facial information aspects accurately and efficiently. Numerous facial recognition-based algorithms have already been suggested, proven successful and deployed (Bouridane, 2009; Baron, 1981; Zhao et al., 2003; Turk and Pentland, 1991) for having automatic attendance as well as the creation of brand-new algorithms, as well as the improvement of some already-existing algorithms or their combination with other approaches, methodologies or algorithms to create facial recognition software (Turk and Pentland, 1991; Slavković and Jevtić, 2012; Tiwari, 2019; Golik et al., 2013). While there have been many advances in the design of facial recognition techniques and systems, several major problems with these algorithms and systems still need to be significantly mitigated or resolved, in order to develop a trustworthy and precise facial recognition-based automatic attendance management system that may be extremely helpful in various domains.

Face recognition is a sub field of Biometric based user identification and recognition. Face recognition has been remained a hot area of research in past two decades. However, accuracy of the face recognition depends on factors like, illumination of light, pose, shadow etc. This paper, presents a simple face detection mechanism based on PCA and ANN. PCA is a technique which reduces redundant data while capturing important features of the considered data.

Literature Survey

Khoi et al., (2016) proposed a local binary pattern-based face recognition system LBP is produce relatively accurate results. The main limitations of LBP are that it does not consider the central pixel while considering local pattern, thus sometime it fails to capture local effects. Kambi-Belli and Guo, (2017) developed a method based on LBP and k-nearest neighbors to overcome the limitations of LBP. Bonnen et al., (2012), proposed a method where face is divided into components and these components are used in face identification with accuracy of 95%. Ren et al., (2013) proposed local ternary pattern-based method which is the advanced version of LBP. Arashloo et al., (2013) proposed face detection method based on various poses. Karaaba et al., (2015) proposed a method based on histograms. Arigbabu et al., (2017) proposed a face recognition method based on face image and local pattern for gender recognition. Leonard et al., (2012) proposed method based on composite correlation filters. Napoléon et al., (2014) proposed a method-based LBP, Heflin et al., (2012) proposed method based on PCA. Zhu et al., (2007) considered face recognition method based on feature correlation filter.

2. PRINCIPAL COMPONENT ANALYSIS

Figure 1 illustrates the fundamental concept of PCA, where PCA is used to compress large-scale images. Faces are represented in databases by the characters I_1, I_2, I_3, ..., I_M and pixel values of each image are kept in a matrix with a size of *MN*. Considering each Face image of size *M*×*N*, thus it contains *M* rows and *N* columns and columns are appended to from one row, therefore total vectors in a row would be *MN*. Vectors are used to store matrices' data. The basic idea behind PCA is to retain only a few dominant terms and discard others. In PCA terms with larger variances are retailed.

The average image is then determined as (Turk and Pentland, 1991)

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} I_i \quad (1)$$

The unique features of each image can be obtained by subtracting each image with mean image.

$$\Omega_i = I_i - \Psi \quad (2)$$

$F_{1\times L} = \mathrm{PCA}[F_{1\times MN}]$, where PCA is an operator applied on original images of size 1×*MN* and PCA reduced image is of size 1×*L*.

Or in vector form for image '*i*' we write as

$$[y_{i1}y_{i2}y_{i3}\ldots y_{iL}] = \mathrm{PCA}[x_{i1}x_{i2}x_{i3}\ldots x_{iMN}] \quad (3)$$

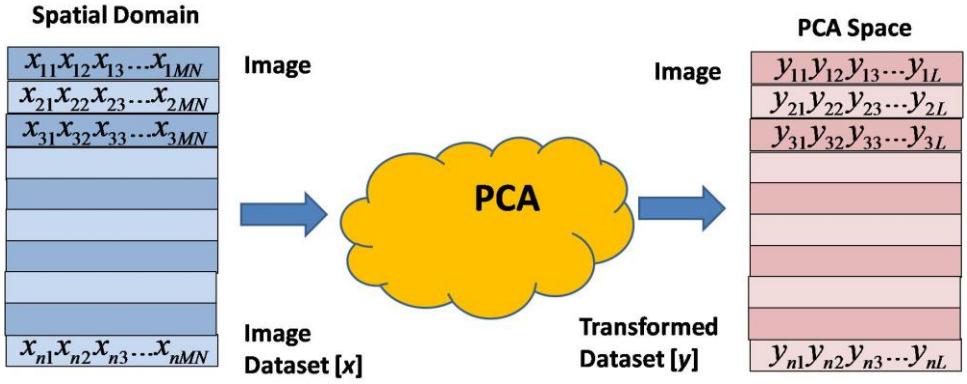

Figure 2 Size reduction in PCA

The pictorial representation of dimension reduction is shown (Figure 2). For covering the variations co-variance is evaluated. It must be note that diagonal element of co-variance matrix are variances while off-diagonal elements are co-variance.

The covariance matrix is calculated as

$C = \Omega\Omega^T$ where $\Omega = [\omega_1, \omega_2, \omega_3, \ldots, \omega_M]$, is created using equation 2.

For matrix $\Omega^T\Omega$, defining Eigen vector as X and Eigen value as λ. Thus, we have

$$\Omega^T\Omega X = \lambda_i X \quad (4)$$

Premultiplying the aforementioned equation by S gives us,

$$\Omega\Omega^T\Omega X = \Omega\lambda_i X = \lambda_i\Omega X \quad (5)$$

Or

$$\Omega\Omega^T(\Omega X) = \lambda_i(\Omega X) \quad (6)$$

Let's define U = ΩX, sometimes referred to as Eigen faces, for the sake of simplicity. These pictures have a ghostly appearance. Eliminating Eigen vectors with zero Eigen values results in another size reduction. The projection of each image (F_K) on face space (ψ) is given by

$$\Sigma = U^T[I_K - \Psi] \quad (7)$$

Recognition of Faces

In the next step, a test image is chosen and PCA projection is applied and Euclidean distance is calculated and image with least distance is chosen mathematically (Figure 3),

$$\Sigma' = U^T[I - \Psi] \quad (8)$$

The Euclidean distance is calculated as

$$d_E^2 = \|\Sigma - \Sigma'\| \quad (9)$$

Limitations of PCA based face recognition

It focuses mainly on the directions with greatest variance.

Just orthogonal transformations (rotations) of the original variables are considered.

A certain number of distributions are not characterized by PCA due to the reason that it is based only on the mean vector and the covariance matrix of the data.
Frontal-view of the image is necessary.
PCA produces incorrect results when it is over-fitted.
Training of images is computationally hard.
Threshold is decided heuristically.

3. ANN BASED FACE RECOGNITION (PROPOSED METHOD)

To overcome PCA's limitations, a new hybrid technique is proposed that uses ANN for user identification and PCA to minimise the dimensions. The flow diagram of the proposed problem is described (Figure 3). In this figure, the input faces of the students are initially read before PCA is utilised to generate the eigenvalues and vectors. The resultant dominating Eigen values are then grouped into a vector and fed into an artificial neural network (ANN), which is then trained. The faces learned by the ANN serve as templates and are used in testing phase. Same procedure is adopted during testing phase. In this structure only a few hidden layers are good enough, as due to the PCA amount of face data is reduced significantly.

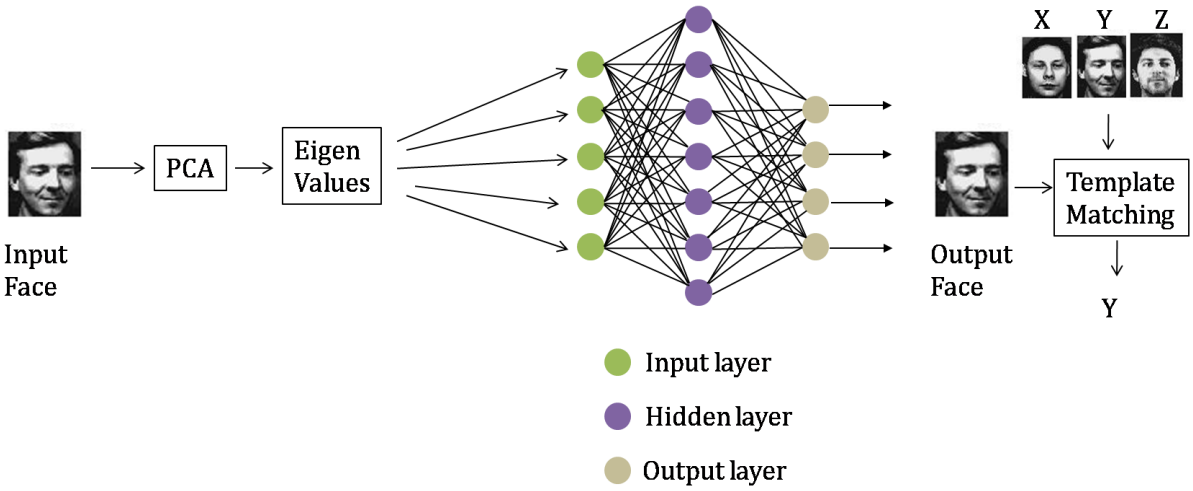

Figure 3 Schematic of proposed method

PCA-based methods cannot reconstruct images and are very dependent on threshold, resulting in very low accuracy. The ideal size of the Eigen vector is also challenging, because using fewer vectors will result in errors in the reconstructed image but faster recognition; on the other hand, using more vectors will result in better reconstruction but a longer processing time.

ANN based Face Recognition steps

The important steps for ANN based face detection are shown (Figure 4).
Step 1: The input image collection is first scaled to ensure that each image has the same size.
Step 2: The face dataset is split up into parts. In this instance, the face dataset is broken up into 15 Groups, each of which contains 10 images.
Step 3: The data are then separated into training, validation and testing datasets. PCA is then used to minimise dimensionality.
Step 4: After that, in the ANN, the number of hidden layers is set. The PCA data make up the same amount of inputs and the outputs total 15.
Step 5: The accuracy of the face detection technique is then assessed.

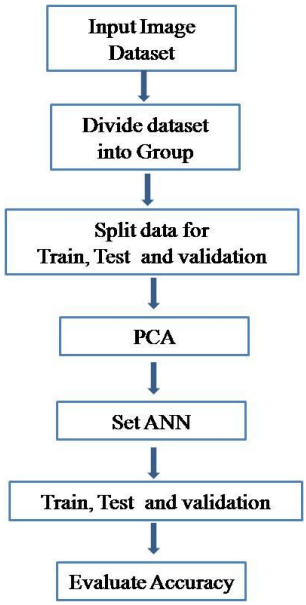

Figure 4 ANN based Face Recognition steps

ANN structure for Face authentication

The basic structure of ANN used in this work is shown (Figure 5), here x_1, x_2 are input which are number of principal components of PCA.

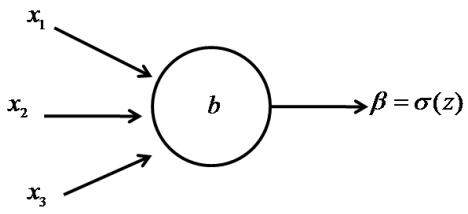

Figure 5 Schematic of ANN structure

Therefore, the output would be of the form $\beta = \sigma(z)$ and $z = \sum_i w_i x_i + b$. In our ANN design, to minimize error gradient descent algorithm is used.

4. SIMULATION RESULTS

In this section simulation results for PCA are presented while considering ORL database and results are displayed while considering 16 image frames, with four images displayed in each row and column. For the considered 16 images, average image is generated which is obtained by taking the average of the considered 16 images (eqn. 1). Mean image represents the common part of all the images and to obtain deviation from each image mean is subtracted. Next Eigen values for 16 images are shown and values are plotted (Figure 6) in ascending order. Referring above formulation Eigen values is λ_i (eqn. 6)

The covariance matrix is constructed next, after which the Eigen-values are calculated. The Eigen values near to zero are then eliminated and the remaining Eigen values are used to calculate the Eigen vector. Lastly, Eigen faces are computed after the normalising of Eigen vectors (Figure 7).

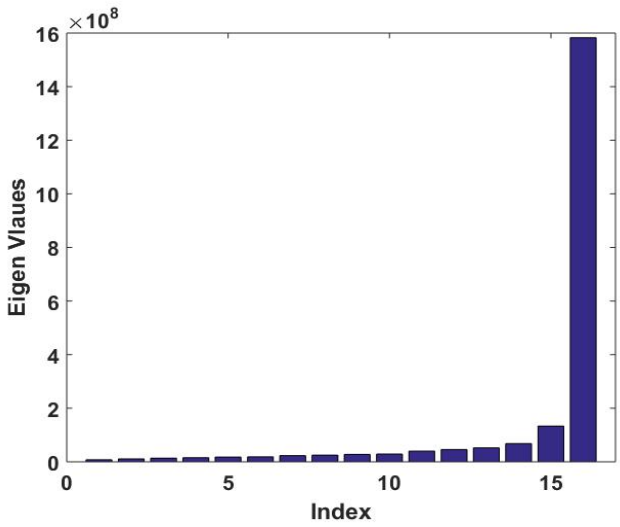

Figure 6 Eigen value vs. image index

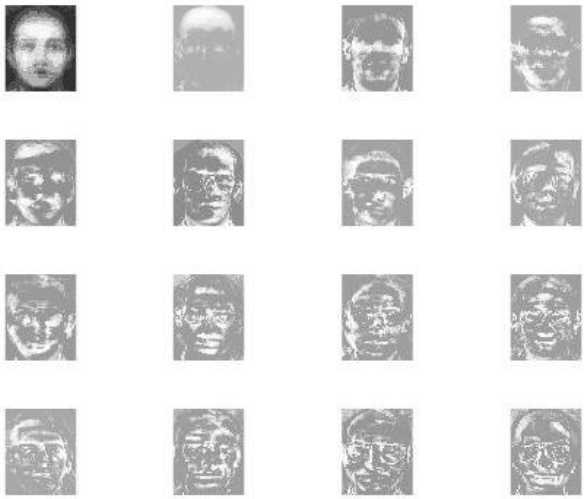

Figure 7 Eigen faces

(a) **(b)**

Figure 8 (a) Original image (b) Reconstructed image

The testing of PCA based face detection is shown (Figure 8), here original image is shown (Figure 8 (a)) and after applying PCA the recognized face in shown (Figure 8 (b)). They look very much similar. In Figure 9, histograms of original and reconstructed

images are shown. It is clear from the figures that the histogram of both the images varies considerably still recognition is possible this is the main advantage of PCA based methods.

In second experiment, another image is considered for testing and re-constructed image is shown (Figure 10). Due to the averaging effect extra baldness near forehead can be observed. Still pace is recognized. Therefore, PCA is susceptible to variations in light and pose, therefore its accuracy is less and accuracy is around 72%.

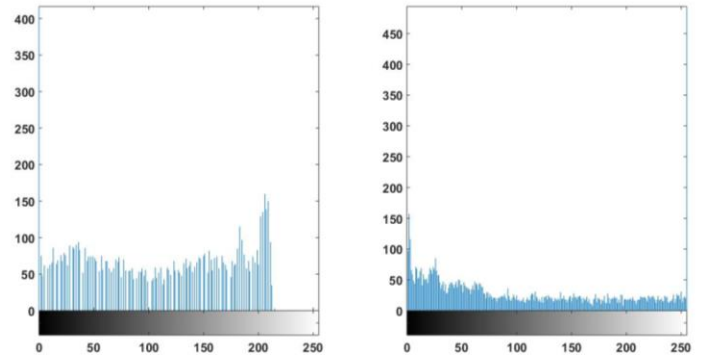

Figure 9 Histogram of (a) Original image (b) Reconstructed image

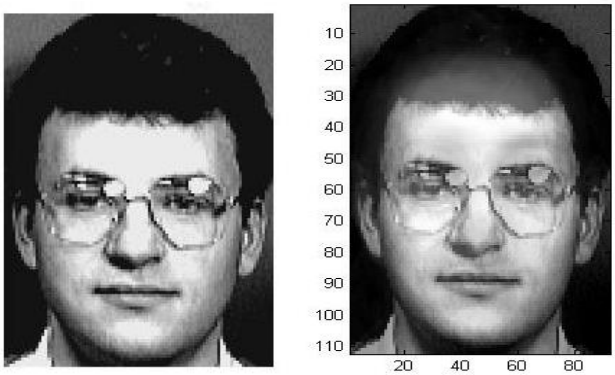

Figure 10 (a) Input and (b) Re-constructed images

ANN based face detection

In ANN based face detection we have considered root mean square and cross entropy for error minimization. First root mean square error is used for evaluation. Here number of inputs which denote PCA data are 100 and as the number of hidden layers are double of inputs i.e., 100×2=200. In Figure 11'*w*' denotes weights and '*b*' is fixed bias. Total outputs are 15 one output for each person.

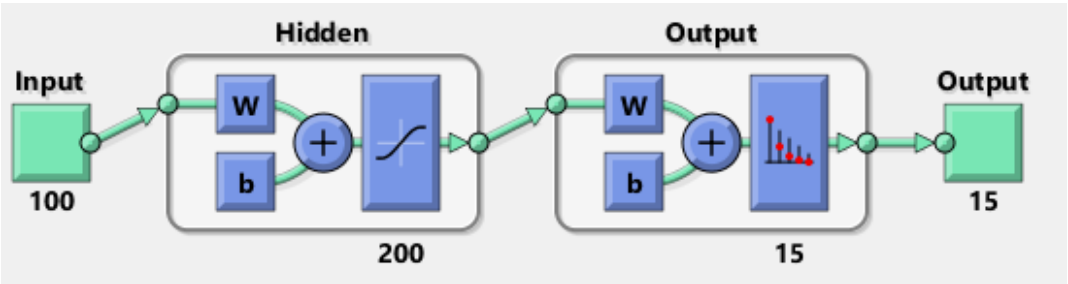

Figure 11 Structure of ANN for face detection (MSE)

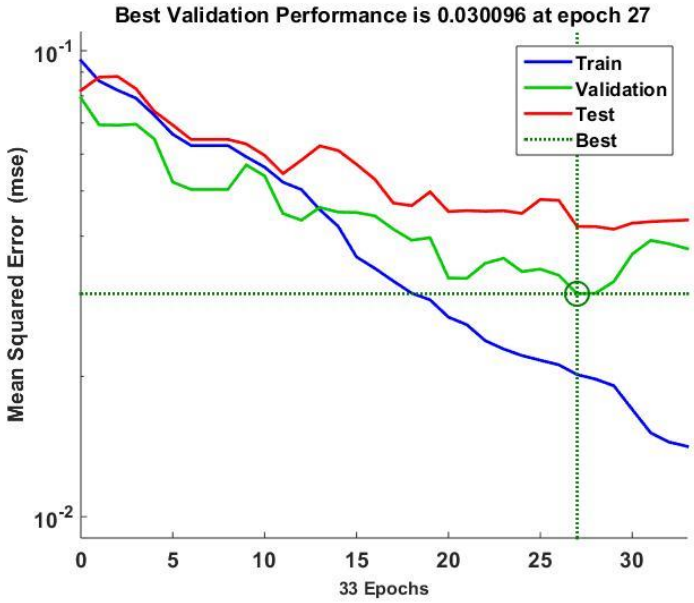

Figure 12 MSE vs. Epochs

The number of times all the training vectors are used just once to update the weights is called an epoch. MSE is plotted vs. epochs for train, test and validation process (Figure 12). MSE for training is at 27 epochs is 0.009 while for testing it is 0.11 and for validation MSE is 0.03, which is minimum for validation process.

In Table 2, accuracy of the notable recent techniques is detailed. For most of the techniques accuracy is between 90 to 95 percent. LBP and LTP techniques have accuracy better than 98% but due to complex nature and larger run time they are not suited for real time applications. The proposed technique in the work has accuracy of 97% with very fast run time therefore can be applied to real time applications. In the proposed method problem of slow learning in ANN at the later stage is tackled by considering cross entropy function.

Table 2 Accuracy Comparison of Face Recognition Techniques

Reference	Technique	Accuracy (%)
Khoi et al., (2016)	local binary pattern	90.96
Kambi-Beli and Guo, (2017)	LBPNet	94.80
Bonnen et al., (2012)	PLBP	91.97
Ren et al., (2013)	Cosine similarity	95.00
Arashloo and Kittler, (2013)	LTP	98.71
Karaaba et al., (2015)	HOG and MMD	68.59
Arigbabu et al., (2017)	PHOG and SVM	88.50
Leonard et al., (2012)	VLC correlator	92.00
Napoleon and Alfalou, (2012)	LBP and VLC	96.40
Heflin et al., (2012)	correlation filter	39.48
Zhu et al., (2007)	PCA–FCF	96.60
Proposed	ANN+PCA	97.01

5. CONCLUSIONS

In this paper, a hybrid face recognition technique based on PCA and ANN is discussed. The PCA algorithm is one of the simpler approaches to facial recognition, despite not being the most accurate. PCA must be employed in place of more exact methods due to the time constraints of real-time systems. The facial recognition programme produced good results, with a few irregularities. The eigenvalues and eigenvectors of an image collection were precisely determined. Accurate face comparison was achieved using the decomposition coefficients. Each face underwent successful user identification and successful user face verification. The only issue is with threshold settings; consequently, ANN is utilised to solve this issue. Together with key design considerations, a thorough

description of the PCA and ANN based face detection technique is provided. The accuracy of prominent methods is finally compared and it is discovered that PCA is the most straightforward to execute with respectable accuracy. When compared to other methods, the accuracy of template matching and HMM-based techniques is superior, albeit at the expense of computing complexity. The method put out in this work, however, is just somewhat difficult and has a 97 percent accuracy rate.

Ethical issues

Not applicable.

Informed consent

Not applicable.

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Conflict of Interest

The author declares that there are no conflicts of interests.

Data and materials availability

All data associated with this study are present in the paper.

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