Forensic Technology Based on Biometrics Application

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Abstract

Human Biometrics have been useful in identifying suspects in forensic investigations, notably in digital forensics. The identification of a person is verified using their biometrics. Because the traditional techniques for a suspect's identification in forensics are no longer accurate and have several flaws, digitalisation was utilised to recognise suspects using images of their biometrics traits. Various techniques were used to recognise and extract features from these images, including continuous and discrete forms of Momentum, algebraic filters, neural networks, and deep learning. Several biometrics have been utilised for this purpose, the most prominent of which we will use in this study are (Face and iris). This is based on databases that include images of multiple people's biometrics. The features of these images are extracted following pre-processing using many feature extractors. This article described a model for a system that stores two types of biometric images for each individual, compares each image to its own dataset, and then recognises and extracts the features of each image. Applied algorithms to extract unique traits for each biometrics used in the search: Face and iris, used a hybrid algorithm of Zernike moment and SVD to identify the facial features and a hybrid algorithm of Legendre moment and LQP to recognise the iris features. The suggested approaches were used in several databases, including ORL and Brazilian for the face, which yielded a rate of 100% and 98% , and CASIA-IrisV4-Interval datasets for the iris, which yielded a rate of 97.29 %.

Keywords: forensics, Biometrics, Face, Iris, orthogonal moments,Legendre Moment, Zernike Momemnt LQP, SVD.

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1. Introduction

An experiential forensic examination is used to determine similarities between the subject of evidence and a particular source; this may result in bias. Excessive influence by external factors during inspection and inspection explains the evidence. Cognitive forensic specialised can be excessive influence by external factors during inspection and inspection to explain the evidence. The final result of a scientific examination must frequently be communicated verbally to a jury or judge. As a result, verbal reasoning is critical in forensics. When a master witness is called to testify about the degree of similarity between a fingerprint and the defendant's unique fingerprint, they must offer a verbal defence based on qualitative and quantitative measurements.

The use of precise biometric features to evidence dates back to a century ago when the concept of a single identifiable proof framework based on biometric, morphological, and anthropometric features was introduced. The automated evaluation of evidence recorded at a crime scene is a point of convergence between biometrics and forensics. This section discusses a few consequences of utilising biometric frameworks in general and the previously defined modalities. The use of biometrics in forensic technology has two distinct effects. Among the significant issues in this sector are data encryption, anti-forensics, wireless technology, and data measurement. Other issues include locating and collecting data, preserving obtained data, and examining and analysing the disaster. At the same time, digital forensics is classified into four main categories: computer, database, organised, and versatile. In forensic science, the usual setting comprises information indicating dissimilar and unfavourable circumstances, implying that planned comparisons across specimens will present a difficult challenge. Legal science databases are difficult to get and use, especially for research reasons.

- Face Recognition System: Facial identification software is a critical aspect of biometrics; it was used in various applications such as identification and validation, further to pattern recognition and image processing areas. Numerous facial recognition systems have been proposed, following the phases outlined in figure (1).

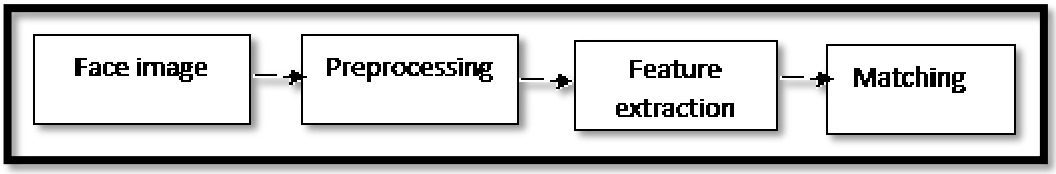

Figure (1) Face Recognition System Steps

- Iris recognition System: is one of the most dependable approaches for person identification in biometrics. Governments have made extensive use of iris identification techniques. The iris is still being evaluated as a biometric feature for law enforcement. Reason iris recognition is not widely used in forensics is that the findings of iris recognition are not interpretable by examiners. Phases of iris recognition as seen in figure(2).

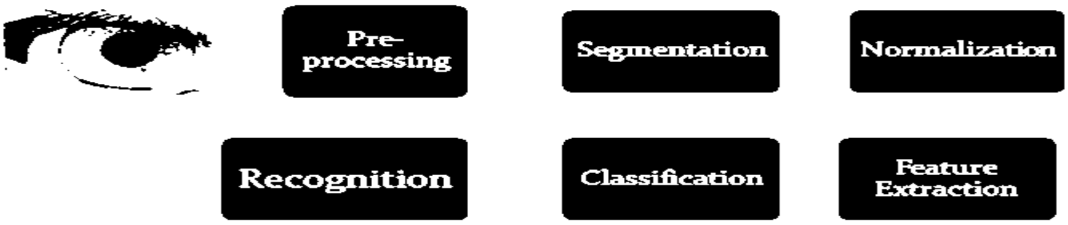

Figure (2) Iris Recognition System Steps

2. Literature review

Christian K. *et al.* (2017) discussed a novel facial transformation modelling approach. The attacks began. I began with an image's lifecycle model. Documents of identification, then, via the image editing registry, expand this form. The model enables an accurate description of processes associated with attack perception, such as specifically for media forensic performance and training and additionally scenario testing for attack detectors. Employ the same features as in a SIFT number to ascertain this reduction. The OpenCV Image Processing Library SURF, ORB, FAST, and AGAST pivotal points in the face area include the following: Additionally to losing cutting-edge information to Canny and operator of the Sobel edge. A decision tree classifier's morphing detection accuracy varies between 81.3 and 98 per cent for various training and test scenarios.

Li Li1 *et al.* (2017), Face recognition has been added as a new method for SIPPP. The technique combines Gabor waves with a feature space transformation (FST) depending on matrix fusion and the nearest running classifier (NNc). To begin extracting trait vectors from an initial training sample Image using Gabor waves. Then, the extracted spatial feature vectors are combined with spectrum-based feature vectors and projected onto a low-dimensional subspace using dimensionality reduction techniques. Finally, NNc can be used to complete the classification process. The proposed method is concise, such as G-FST. On ORL, Yale, and FERET, the G-FST method's performance is evaluated.

D. Ramos *et al.*(2017), Described the problem of forensic evidence interpretation. Based on the results of the biometric system's calculations. Forensic biometrics is the name of the field. It emphasises the importance of the topic by providing some basic forensic science ideas related to interpreting results before they are presented in court, which is becoming more common. Probability ratios are used to process it (LR). Discusses LR Methodology, using a biometric fingerprint system as an example for fingerprint assessment evidence under forensic situations. By using GCDB and cross-validation. Multiple LR Modes. In terms of discriminatory power and calibration performance, they have been proposed and compared

In this study, B. Kaur et al. (2017), Zernike moments and polar harmonic transitions are utilised to recognise the iris in an unsupervised environment employing a nonstop feature set of turn, noise, and light. Each is inferred from CASIA-IrisV4-Interval, IITD. V1, UPOL, UBIRIS.v2, and IIITD-CLI localised iris districts up to the 15th rank on five freely accessible databases are utilised. Concerning future working characteristics curve, exactness, rise to error rate, and selectability record, the recommended method outperformed current advances accessible within the writing in near-infrared and unmistakable images procured from different iris sensors

A. Górniak *et al.* (2017) proposed a strategy of object classification based on the groupings of Zernike moments. The strategy takes advantage of Zernike moments' pattern recognition properties and applies them to the issue of classification. The proposed strategy gives for a vigorous, turn and interpretation invariant classification of complex objects in grayscale images since the particular traits of the classified things are carried over to the Zernike moments. Each object class contains a reference Zernike moment sequence utilised as the class model in this strategy. The object's to the class are determined using the MSE of the object's Zernike moments sequence and the class's reference Zernike moments grouping. Grayscale images of handwritten digits and tiny fragments are used to evaluate the method.

Bineet Kaur's (2019) article offers a discrete torque-based orthogonal constant feature set composed of extracted Tchebichef, Krawtchouk, and Dual-Hahn moments from a spot iris area to capture the iris tissue's local density distributions. Proposed techniques' performance is evaluated against four publicly accessible iris plagiarism databases: IIITD-Contact Lens Iris, IIITD Iris Spoofing, Clarkson LivDet 2015, and Warsaw LivDet 2015. For the IIITD-CLI data sets, a detection rate of 100 per cent for textured contact lenses was achieved, while 99.48 per cent for the Clarkson data sets.

M.Nazarkevycha *et al.* (2019), A novel Ateb-Gabor filter has been created that can reduce the influence of noise greatly. The new filter approach has a considerably larger filter selection. Because it is based on the ATIB function theory, which expands on simple trigonometry, the number of usage alternatives can be expanded to 2900. Furthermore, it allowed for the development a novel method of picture processing. Python was used to solve the nonlinear system of the differential equation. For different m and n parameters, a graphical depiction of the solution is presented. The use of these factors can increase the filtration result's control.

M. Ayyad *et al.* (2019) proposed an unused combination of two projections that employ the discrete waveform transform based on facial recognition algorithms (DWT). Discriminant examination (RW-LDA) and singular value decomposition (SVD) utilise left and right singular vectors. Min-Max, Z-score and Min-Max, Z-score were utilised within the think about on two critical face datasets. Concerning acknowledgement rate and preparing term, the combination of SVD/LR (left and right single vectors) and RW-LDA created the most prominent comes about compared to similar methods detailed within the writing.

Arun R. *et al.* (2020), the author, talks about the latest digital forensic blueprints for vital audiovisual data that smart city applications can use. Additionally, smart devices equipped with biometric authentication can provide security and a customised experience for end-users by verifying the user via face, fingerprint, or voice and demonstrating how vital data obtained by the devices can be manipulated.

T. Dhieb *et al.* (2020) presented a biometric-based document recognition system to identify an author for forensic document inspection. In the initial step of this method, online handwriting is pre-processed and segmented into a sequence of strokes. Then extricate a set of static and dynamic features from each stroke. After that, all sections of two sequential strokes are separated into bunches and subgroups based on their position and geometric properties. At last, as a classifier, a Deep Neural Network is utilised. On Latin and Arabic characters, tests on the IBM UB 1, IAM OnDB, NLPR Handwriting, and ADAB databases appear that the proposed strategy beats existing author distinguishing proof procedures. This illustrates its utility in forensic handwriting analysis, the advancement of a modern online script and a free multilingual writer recognisable proof system for looking at forensic reports. Hence, proposed an unused worldview that employments foggy perceptual components to portray writers' handwriting.

3. Methodologies

The majority of proposed algorithms concentrated on determining who extracts the most critical qualities and how to utilise them to acknowledge them. Numerous feature extraction approaches have been developed to accomplish these objectives: Legendre, Zernik. These times are typically constant when confronted with common difficulties such as translation, measuring, or any other type of difficulty. Rotate the procedure concerning the captured image. Numerous instances, such as those in Zernike and Legendre, comprise an orthogonal base set that may represent a small number of images with a high degree of detail. Orthogonal polynomial assumptions have been utilised and can be employed. The most important quality of moments is their sensitivity to image details; hence, they are well-suited for expressing image features. Typically, moments employ a variety of alternative orderings to get many feature vectors.

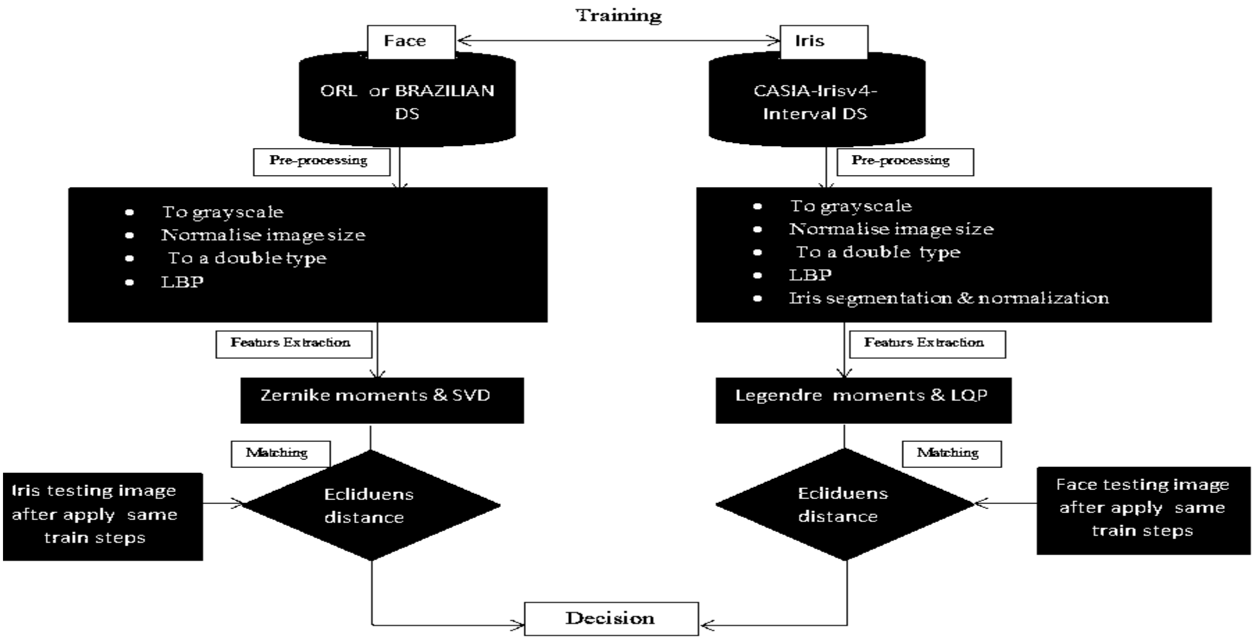

Figure (3) Proposed System Methodologies Diagram

3.1 Pre-processing

These are the phases of image processing and erasing its processing by performing various operations such as noise removal and edge detection to prepare the image for features extraction.

3.1.1 Face

converted the incoming image's colour format to grayscale at this step. Normalise the image to the face image size by specifying a fixed size for all input images and converting faces (training and testing) to a double type to simplify computations and minimise dimension. A face image is partitioned into a set of regions similar to our proposed system as a non-overlapping method(Local Binary Patterns).

The LBP feature vector is produced in the following manner.:

- The window is divided under examination inside cells (each cell 16 *16 pixels).

- Calculate the distance between each cell pixel and eight neighbours for each of its (top-left, middle-left, bottom-left, top-right, ...), clockwise or anti-clockwise direction are circumnavigate the pixels.
- When the centre pixel's value is larger than the adjacent pixel's value, enter "0." Alternatively, you may type "1". Consequently, an eight-digit binary number is generated (Generally, decimal values are converted for convenience).
- Create a histogram for the frequency of each "number" occurring within a cell (i.e., a combination of pixels that is greater and smaller than the centre). As a feature vector, 256-dimensional may be seen in this histogram.
- Normalise the histogram if desired.
- Concatenate all cell histograms (normalised). As a consequence, a feature vector for the full window is created.

Using a support vector machine, an extreme learning machine, or another machine learning approach, the feature vector may now be used to categorise images. These classifiers can be used to recognise faces or to analyse texture.

3.1.2 Iris

First, transform the colour format of the entering image to grayscale. To simplify computations and decrease dimension, normalise the image to the size of the iris image by defining a constant size for all input images and converting all images to a double type. After that, segmented and normalised.

a) Iris segmentation

The initial stage in iris identification is determining the iris-sclera and iris-pupil boundaries. The Circular Hough Transform (CHT) was used to accomplish this, which recognises circles in images and is immune to noise.

$$\mathrm{CHT}(\mathrm{xc},\mathrm{yc},\mathrm{r}) = \sum_{i=1}^{n} \mathrm{CHT}\,(\mathrm{xi},\mathrm{yi},\mathrm{xc},\mathrm{yc},\mathrm{r}) \quad ...... (1)$$

where (Xi, Yi), I = 1,2,3,.....n are the image's edge points. The image is converted to a binary edge map using the Canny edge detector in which each edge point is represented by the centre of a circle of varying radius. CHT is used to detect the iris, the biggest circle with the most edges. An accumulator is used to hold the circumferential pixels. When CHT (Xi, Yi) sits on the circle's perimeter, CHT (xc, yc, r)=1 is stored in the accumulator; otherwise, CHT (xc, yc, r) = 0 is saved. The accumulator's maximum value corresponds to the iris's centre coordinates.

b) Iris normalisation

Due to light fluctuation and data collection at variable distances, segmented iris samples are converted to fixed dimensions. To normalise segmented iris samples, the Daugman's homogeneous rubber sheet model is utilised, which translates the segmented iris image F (x, y) to polar coordinates (r,θ), where r is between [0, 1], θ is between [0, 2].

$F(x(r, \theta), y(r, \theta)) \rightarrow F(r, \theta)$ ..... (2)

$x(r, \theta) = (1-r)x_p(\theta) + rx_I(\theta)$ ..... (3)

$y(r, \theta) = (1-r)y_p(\theta) + ry_I(\theta)$ ..... (4)

The coordinates x_I, y_I and x_p,y_p denote , the iris and pupil .

3.2 Feature extraction

This stage is one of the phases of identifying biometric images; it is when the features of the images being compared are extracted.

3.2.1 Face

Several approaches were used to extract the features of the images in the recognition processes, such as moments, filters, etc., and explain the approaches used in this research to extract the features of the face image as follows:

a) Zernike moments

In their simplest form, moments calculate a numerical value at a certain distance from a reference point or axis. Zernike polynomials are a group of orthogonal polynomials defined on the unit disc, while the Zernike moment is defined as the image function's projection onto these orthogonal basis functions. It has been demonstrated that Zernike moments are more resilient in noise presence. Because their moment functions are constructed in terms of the image space's polar coordinate representation, Zernike moments are frequently utilised in recognition tasks that require rotation invariance. Zernike moments are an excellent feature representation because they give more information on the facial image attribute and reduce the feature vector's dimensionality, which leads to improved outcomes. The implementation of Zernike moments is discussed in; Sun-Kyoo Hwang modified several formulae. The following definitions apply to Zernike moments for images with intensity f (r, θ) of order p and repetition q.

$$Z_{pq} = \frac{p+1}{\pi} \int_0^{2\pi} \int_0^1 R_{pq}^*(r) e^{jq\theta} f(r,\theta)\, r\, dr d\theta, \quad |r| \le 1 \qquad ..... (5)$$

By the following equation, the radial polynomial $R_{pq}(r)$ is denoted:

$$R_{pq}(r) = \sum_{k=0}^{\frac{p-|q|}{2}} (-1)^k \frac{(p-k)!}{k!\left(\frac{p+|q|}{2}-k\right)!\left(\frac{p+|q|}{2}+1-k\right)!} r^{p-2k} \qquad ..... (6)$$

with $0 \le |q| \le p$ and $p - |q|$ is even.

Finally, the Zernike moment is defined as:

$$Z_{pq} = \lambda_Z(p,N) \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} R_{pq}(r_{ij})\, e^{-jp\theta_{ij}} f(i,j) \qquad ..... (7)$$

where:

$$\left.\begin{aligned} r_{ij} &= \sqrt{x_i^2 + y_j^2}\,; & \theta_{ij} &= \tan^{-1}\left\{\frac{y_j}{x_i}\right\} \\ x_i &= \frac{2i}{N-1} - 1\,; & y_j &= \frac{2j}{N-1} - 1 \\ \lambda_p(p,N) &= \frac{p+1}{N-1} & & \end{aligned}\right\} \qquad ..... (8)$$

b) Singular Value Decomposition (SVD)

SVD based technique with an acceptable recognition rate that employs singular values as the feature extractor. Linear algebra produces the singular value decomposition. It plays an intriguing and vital role in a wide range of applications, including image compression, face recognition, signal processing, object identification, texture classification, etc. The unique property of SVD is that it may be applied to any actual matrix. svd of a rectangular matrix A is of the following form:

$$A = USV^t \quad \ldots\ldots (9)$$

A is a m x n matrix, U is a m x m matrix, and V is a n x n matrix. Matrices U and V are orthogonal. An orthogonal matrix is a square matrix A having real entries and obeying the constraint A-1=At. S is a diagonal matrix with m x n singular values on the diagonal.

$$\boldsymbol{AA^t} = \boldsymbol{USV^t}(\boldsymbol{USV^t})^{\boldsymbol{t}} \quad \ldots\ldots (10)$$

$$= \boldsymbol{USV^tVSU} = \boldsymbol{US^2U^2}$$

Also

$$\boldsymbol{A^tA} = (\boldsymbol{USV^t})^{\boldsymbol{t}}\boldsymbol{USV^t} \quad \ldots\ldots\ldots\ldots (11)$$

$$= \boldsymbol{VSU^tUSV^t} = \boldsymbol{VS^2V^2} \quad \ldots\ldots\ldots\ldots (12)$$

As a result, V and U are computed as the eigenvectors of ATA and AAT, respectively. The singular values along the diagonal of the matrix S are the square root of the eigenvalues. A is a real matrix, and the singular values are always integers.

3.2.2 Iris

Following the pre-processing of the iris, extracting the features begins, and numerous approaches have been employed to do this. The following methods are used in this article:

a) Legendre Moments

Teague introduced Legendre moments are moments whose core function is the Legendre polynomials. Legendre moments are orthogonal moments used in various applications of pattern recognition. Used to produce near-zero redundancy in a set of moment functions by mapping the moments to the image's independent features. The image intensity function is projected onto the Legendre polynomial to define the Legendre moment[20,17]. Two-dimensional Legendre degree moment (p + q) using image intensity function $f\ (x, y)$ is defined as

$$\lambda_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p_p(x)p_q(y)f(x,y)dxdy \quad \ldots\ldots\ldots\ldots (17)$$

A discrete version of the Legendre moments can be shown as:

$$\lambda_{pq} = \frac{(2p+1)(2q+1)}{(M-1)(N-1)} \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} p_p(x)p_q(y)f(x,y)dxdy \quad \ldots\ldots\ldots\ldots (18)$$

The Legendre polynomial Pp (x) is a perfectly orthogonal basis set in the interval [-1, 1] Where p, q = 0,1,2,3, ..., ∞:

$$\int_{-1}^{1} p_p(x)p_q(y)dx = \frac{2}{2p+1}\,\delta_{pq} \qquad \text{............ (19)}$$

The Legendre polynomial of nth-order is expressed as:

$$p_p(x) = \frac{1}{2^q}\sum_{p=0}^{\frac{q}{2}}(-1)^q \frac{(2q-2p)!}{p!(q-p)!(q-2p)!} X^{q-2p} \qquad \text{........... (20)}$$

b) Local Quantized Pattern (LQP)

Hussain and Trigges introduce a new local pattern approach for visual identification called Local Quantized Pattern. It inherits some of the flexibility and power of local pattern ones without increasing the run-time or complexity. The use of larger local pattern neighbourhoods significantly increases the number of pixels in diagonal (D), and anti-diagonal (A), vertical (V), horizontal (H) pixel directions, as well as a group of these such as diagonal-ant diagonal (DA), -vertical-horizontal (VH), and vertical-horizontal-diagonal-anti diagonal (VHDA). Similarly, demonstrates how the concept of LBP was used to develop directional local patterns (DLEP). The spatial structure of the local texture is denoted by BLEP utilising the local extrema of the centre pixel Ic. In DILEP, the local extrema 45°, 90°, and 135 ° degrees were determined for a given picture by computing the local difference between the centre pixel and its neighbours.
Hassan Mahammed provided a straightforward implementation of the Local Quadrant Pattern based on the concepts of LTP and DLEP.
Let l*c* and I*i*, (i = 1,2,...., 8) indicate the centre pixel's and neighbours' intensities, respectively. First, determine the difference between the centre pixel (lc) and each adjacent pixel (Ii) using the formula below.
$D_i = I_i - I_c; i = 1,2,\dots 8$
Next, each pair of results Di for a certain direction will be combined into a single vector to form a line. (e.g. I_2, with I_6, in one line), according to the following eq. (21).

$$p_\alpha = F(D_j, D_{j+4}); j = (1+\alpha/45), \forall\alpha = 0°, 45°, 90°, 135° \qquad \text{.......... (21)}$$

Then, determination values are calculated using the threshold "(t)" as defined in the following eq. (22).

$$F_i \begin{cases} 3 & |p_{i1}| > t \cap |p_{i2}| > t \cap \text{sign}\,(p_{i1}) \neq \text{sign}\,(p_{i2}) \\ 2 & |p_{i1}| > t \cap |p_{i2}| > t \cap \text{sign}\,(p_{i1}) = \text{sign}\,(p_{i2}) \\ 1 & |p_{i1}| \leq t \cap |p_{i2}| \geq t \cup |p_{i1}| \geq t \cap |p_{i2}| \leq t \\ 0 & \text{else} \end{cases} \qquad \text{.............. (22)}$$

$$i = 1,2,\dots 4$$

Where F i is the sum of the values in each line, finally, convert these values to decimal numbers to obtain the new LQP value for the central pixel by eq. (23).

$$LQP_{\text{row}} = \sum_{i=0}^{row-1} F_i \times 2^i \qquad \text{................ (23)}$$

4. The Proposed System

The suggested approach utilised separate training algorithms for each vital biometrics to perform the recognition procedure. Each algorithm is briefly described below:-

Training Algorithm: The term logging or training algorithm refers to the steps taken. The following stages are included when the suggested method is applied to the whole set of images.

Algorithm(1): face Training Algorithm
Input: images of a train.
Output: faces features.
begin: 1: Read the images to learn from the dataset. 2: pre-processing operations include: 2.1: Conversion of colour to a grayscale image. 2.2: Data Converter to double. 2.3: resized for output of 2.2. 2.4: Employ a canning filter edge detector, consider the resulting image I. 3: Operations of the features extraction stage are : 3.1: Use the LBP method to generate an array of neighbours called I. 3.2: Perform SVD on M to generate matrices, then choose the S matrix and save the results in a vector named R1. 3.3: Performing the Zernike moment on I creates an array, which is then converted to a vector named R2. 4: Concatenation of vectors R1 and R2 to create a single vector called A, used as one row in the final array. 5: save the generated array and any needed parameters to a file that will be loaded into the testing Algorithm. End

Algorithm(2): Iris Training Algorithm
Input: images of a train.
Output: features of iris.
begin: 1: Read the images to learn from the dataset. 2:Pre-processing operations are : 2.1: convert a type of image to grayscale. 2.2: Data Converter to double. 2.3: resized for output of 2.2. 2.4: Applying segmentation and normalisation 3: a process of features extraction includes: 3.1: Performing LQP on I generates matrix. The array results are then stored in a separate vector labelled R1 3.2: Employ the Legendre moments on I to generate an array of neighbours called R2. 3.3: Performing Legendre moments on R! generates an array, which is then stored in a separate vector labelled R3. 4: Concatenate vectors R2 and R3 to create a single vector named B. This vector will take up a single row in the final array. 5: Save the resulting array and the necessary parameters to a particular file. It will be incorporated into the testing algorithm. End

Test algorithm: The term test algorithm refers to the steps applied to a single image. It was entered into the system, and the results were compared. We developed a single test algorithm for multi-biometrics by choosing three images at a time, one for each of a person's biometrics. The steps are as follows:

Algorithm(3): Testing Algorithm
Input: Images face & iris .datasets, e.g. Brazilian or ORL datasets, CASIA-IrisV4-Interval datasets.
Output: Identification person.
begin: 1: Testing images are Read 2: Compare the similarities using a defined threshold; if the resultant coefficient is less than or equal to the threshold, go to the next step; if not, the Ending algorithm.

3: Apply steps 2-4 of the training algorithm for each vital image.
4: The proposed approach used Ecliduens distance to choose the vector that belongs to the nearest image for classification. This distance depends on the smallest distinction between the feature vectors for training images and testing images.
End

5. Environments

The proposed algorithm was applied to three main datasets: ORL. This database has four hundred images, including images of forty individuals, each with ten different shots of their faces. The type of image is an index. FEI, This dataset is divided into three groups, each of which has seven hundred images of fifty individuals. Each individual within a group has fourteen shots for a face, and the last image is in low light. CASIA-IrisV4-Interval datasets for the iris, a database of images of the irises of the eyes of thirty-seven persons, including five shots for each eye (right and left).

6. Discussions

Additionally, the FEI environment is extremely difficult to navigate because of the scene's many elements, necessitating the necessity for since several pre-processing procedures are performed, the recognition rate may be lower than that achieved by applying the suggested method, the ORL. In certain instances, anticipating particular identification is difficult and, in some instances, regarded as challenging. The hybrid method handles a number of the issues and obstacles associated with noise, illumination, etc. As with iris database images containing noise and needing more pre-processing, hybrid and edge detection such as segmentation and normalisation of the image for the algorithms to extract its features.

7. Conclusion

Various algorithms are utilised in this article to process multiple biometric images of an individual. The last point of emphasis This article discusses the use of biometric images to identify a suspect in a forensic case or inquiry. Several biometric photos are extracted from the study databases, which serve as the foundation for the face and iris. Classifying them and extracting their features using numerous property extractors, including a hybrid technique that combines Zernike moments and SVD to extract the features of facial images and the Legend Moment and LQP of the iris. After applying the algorithms to many datasets, they offered promising results. Thus, we were able to present a biometric model that can be applied and used on suspects' forensic biometric databases, such that when a new biometric image differs from that used in the model and is compared to the databases after applying the model's methods to analyse and compare the image features with the database images using Euclidean distance matching algorithms. Similarity enables the model to determine if the individual's input biometrics images exist in forensic databases or not, and hence whether a suspect in the case or investigation.

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