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EFFICIENT PERSON RECOGNITION BASED ON BIMODAL BIOMETRIC TRAITS

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ABSTRACT

This paper proposes a method for efficient person recognition using bimodal biometrics, which has practical applications in various fields. The method involves integrating two different biometric traits, such as fingerprints and facial recognition, to enhance accuracy and security. The fingerprint part in an image is cropped, and Histogram Equalization (HE) is applied. The cropped HE image is resized to 400 x 400, and Discrete Wavelet Transform (DWT) transforms into low and high-frequency bands. The low-frequency LL-band of size 200 x 200 is considered by discarding the high-frequency bands of LH, HL, and HH to reduce noise and dimensionality. The LL band coefficients are converted into column vectors to obtain final features. The Euclidean Distance (ED) compares test fingerprints with database fingerprints to compute performance parameters. The face recognition is based on a modified power law transform and the Viola-Jones algorithm. The Double Density Dual Tree Discrete Wavelet Transforms (DDDTDWT) extract features. The ED matches the obtained features of the database and tests face images to compute performance parameters. The computed Percentage Recognition Rate (PRR) for fingerprint and face recognition systems are fused using the Bayesian theorem. It is seen that the recognition rate of the proposed method is better compared to the unimodal biometrics.

Keywords: Biometrics, BI-Modal, DWT, Fingerprint, Face Images, Fusion

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1. INTRODUCTION

The ability to prove one's identity is crucial in today's digital environment. Driver's licenses, ID cards, and other traditional forms of identity are vulnerable to loss, theft, and fabrication. Furthermore, losing or having these physical documents taken can result in identity theft or illegal access. On the other hand, biometric authentication is a safe identification method that is intrinsic to each person and difficult to duplicate. The development of biometrics has mitigated traditional issues of identifying systems. Enhancing security for real-time applications is the aim of developing biometric systems. The foundation of biometrics, a human identification and verification technique, is the distinctive behavioral and physiological traits that enable successful individual differentiation. A person's physiological traits include iris, palmprints, fingerprints, face patterns, and deoxyribonucleic acid (DNA). These qualities are frequently employed due to their durability, affordability, and originality. Behavioral features are traits, including body language, handwriting, signatures, speech, and keystrokes, that are connected to a person's behaviors. These characteristics are unpredictable and unproven because they rely on an individual's surroundings and mindset.

Although biometric technologies have numerous benefits over antiquated old methods, they also have disadvantages. By combining the data transferred between the matcher and the stored template, an attacker can alter a real person and bluff a person's uniqueness. If criminals require it, they can also alter the data in the template [1]. Biometric recognition systems have gained appeal due to the development of several practical, intriguing, and widely recognized applications, including sanctuary worries, investigation, legal inquiries, fake talents, self-access administration, and entrée regulators. Multimodal biometric systems employ two or more biometric traits and are more robust, dependable, and resilient in a dynamic setting [2]. The methods of feature stage blend, decision stage combination, and score stage combination are all combined in multimodal biometric systems. Identification and verification are the two techniques utilized in biometric applications. In verification mode, a one-to-one (1:1) comparison between the deposited sample and the test biometric trait confirms a person's identity. In identification mode, each sample contributed to the dataset or one-to-many comparisons (1: N) are compared to the test biometric characteristic to verify the individual's identity.

Because fingerprint images are inexpensive, highly accurate, and simple to get using simple tools, they are widely employed in human search operations. The elements of image orientation, ridgeline flow, minutia points, spatial domain features, transform domain features, and Gabor filter responses constitute the basis of most fingerprint classification techniques [3]. It is difficult and performs poorly to obtain high-quality fingerprint photos of greasy, filthy, and wet hands using sensors. Face recognition is more convenient and cost-effective than other biometric recognition, such as fingerprint and iris recognition, since it does not require special equipment to acquire face images [4, 5]. In addition, with the recent significant development of deep learning, face recognition performance has been dramatically improved [6]. A state-of-the-art technological development, the facial recognition system is intended to effectively and precisely identify people by facial features. Facial recognition has become commonplace in today's more technologically advanced society, with uses in various fields, such as intelligence operations, security protocols, public records management, authentication procedures, and many other surveillance systems. Notably, facial recognition has become much more effective, especially with the introduction of deep learning techniques [7]. However, despite these developments, the effectiveness of these methods is still hindered by intrinsic constraints of face image data, including different lighting conditions, facial postures, facial expressions, occlusions, disguises, time variations, and image quality fluctuations [8].

Face recognition establishes a person's unique identity through facial characteristics, infested with factors like inadequate illumination, poor contrast, loss of specificity, low resolution, and external environmental factors. There is a need to counteract these error-inducing factors to enhance the image quality, which aids in better feature extraction.

A single-modality biometric-based authentication system is unreliable because when the information from the related modality is covered, the authentication's performance suffers. For instance, the effectiveness of face identification is hindered by face masks [9]. This limitation underscores the need for a bimodal biometric system, which uses two traits for efficient recognition and is believed to be intrinsically more robust to spoof attacks.

A Standard Biometric Properties Physiological or behavioral characteristic must satisfy the following requirements for each individual [10]:

(i) Universality: The application must be accessible to all users through biometric features.

(ii) Individuality: Everybody has a unique biometric characteristic.

(iii) Permanence: The biometric trait must remain unchanged over time.

(iv) Measurability: Sensors must be able to collect and digitize each person's unique biometric profiles.

(v) Performance: There should be limited False Acceptance Rate (FAR) and False Rejection Rate (FRR), and overall accuracy should be reasonable.

(vi) Acceptability is the degree to which people agree that a particular biometric system is necessary and are prepared to supply biometric information.

(viii) Circumvention illustrates how affected biometric characteristics can get past the system

Contribution: This research suggests using fingerprints and facial photos for efficient person recognition based on bimodal biometric traits. The DWT extracts features from fingerprint images, and the DDTDWT extracts features from face images to verify the performance of biometric systems. The performance parameter PRR is computed for fingerprint and face recognition systems and fused using the Bayesian theorem to obtain bimodal biometrics results.

Organization: Section 2 explains the paper's preparation as a literature review of current face and fingerprint recognition methods. Section 3 provides an in-depth discussion of the suggested methodology. Section 4 compares and discusses the experimental results with those of unimodal biometrics. In section 5, the research article comes to a close.

2. LITERATURE SURVEY

This section identifies people using fingerprint and facial recognition methods created by multiple researchers using various techniques.

2.1. Fingerprint Recognition

Li et al. [11] suggested a productive UAV identification method that uses machine learning and the discrete wavelet transform coefficients of differential signals (D-DWT). During the detection phase, the system uses correlation detection and energy changes to retrieve each signal frame's preamble information. The feature extraction phase examines the impact of carrier frequency offset (CFO) on identification accuracy. Additionally, the anti-interference performance of the DWT coefficients is examined by transforming the differential signals into the wavelet domain. A fingerprint method utilizing the Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT), and Discrete Wavelet Transform (DWT) was introduced by Dale and Joshi [12]. Around the core point, a 64x64 fingerprint image is gathered. To obtain the feature vector in terms of standard deviation, the transforms are applied to the gathered image, and the factors are arranged in a particular manner.

The Euclidian distance serves as the basis for the fingerprint equivalent. A fingerprint augmentation method based on DWT, PDE, and SVM was proposed by Singh and Girdhar [13]. The LL, HL, LH, and HH bands of the fingerprint are obtained using the DWT. Using a 3x3 window, the focal point of each ridge is chosen in order to recover the fingerprint's fine details. The minutiae method gives the PDE algorithm the best characteristics. Unique features are classified using the SVM.

Shinde and Annadate [14] used DWT and singular value decomposition (SVD) to examine a person's relationship to gender. By mining the energy computed from all of the DWT bands combined with the spatial features of non-zero singular values obtained from the SVD, gender-based classification is achieved. K Nearest Neighbor (KNN) does the matching.

Three modalities—face, fingerprint, and palm vein—were used in the multimodal biometric system that Tekade and Shende [15] suggested for personal identification. Face, palm vein, and fingerprint features are extracted using the minutiae, DWT, and Local Binary Pattern (LBP) processes. In order to get the final features for algorithm testing, feature-level fusion is used. Rezaei and Abaei [16] investigated the use of DCT, DWT, and moment techniques for fingerprint recognition based on hybrid features. For classification, a backpropagation neural network is used. The Gray Level Co-occurrence Matrix (GLCM) and DWT methods were investigated on fingerprint photos by Cevik et al. [17].

The size of features is compressed using the DWT. In order to acquire a comprehensive and low-dimensional representation of the building image, Zhao and Liu [18] presented a building recognition model that uses a multi-scale GIST feature illustration notion. In order to show the position connection of local grids, Yangyang Wang et al. [19] projected the GIST descriptor, which imprisons the achievement's structural information and its trajectories. The bag of words technique is used to build word phrases after the GIST traits are divided into four sectors. It makes use of the SVM classifier. A system for human behavior in still photos based on LLC and GIST features was introduced by Ende et al. [20]. By segmenting the image into blocks and building the Gabor filter collection of 32 scales and directions, the GIST characteristics are assessed. Each block's features are combined and adjusted for the GIST features. The SVM is employed in the classification process. In order to reduce noise before extracting features from the GIST descriptor, Vinay et al. [21] suggested a double-filtered GIST-based descriptor for face recognition that uses edge detection using the Prewitt approach, DCT, and IDCT conversion.

2.2. Face Recognition

Gururaj et al., [22] studied a wide range of these methods, and Face Recognition (FR)-related issues are examined in this work. FR systems were prominently implemented after analyzing the current solutions from the standpoints of several inputs, including illumination, position variation, facial expressions, occlusions, and aging. This survey's main contribution is thoroughly examining cutting-edge FR techniques and the taxonomy developed to group them into different classifications, ranging from hybrid approaches to appearance. A thorough classification of image and video-based FR techniques is also provided, emphasizing the key developments and essential processing processes for managing massive volumes of datasets. Additionally, the proposed extensive analysis highlights the important aspects utilized by the most recent research conducted in FR. Zhang et al., [23] proposed using the knowledge distillation method to improve poor face recognition performance by using a texture-guided (TG) transfer learning strategy. Instead of using forward propagation to construct distillation loss, as is the case with output logits and intermediate features, this study uses the gradient texture of backward propagation.

Specifically, in order to reduce the feature difference between high- and low-quality images, the gradient texture of the former needs to be aligned with the latter. Furthermore, by adding attention, a soft-attention (SA) variant of transfer learning, called SA-TG, is created to focus on informative regions.

Terhörst et al., [24] provided a training-free method for evaluating a face image's pixel-level characteristics using an arbitrary face recognition network. To do this, a sample-specific quality regression model is constructed using an estimated model-specific quality value of the input image. Quality-based gradients are back-propagated and transformed into pixel-level quality estimates using this technique. Maafiri et al., [25] proposed Local Binary Pattern and Wavelet Kernel PCA (LWKPCA), a novel feature extraction technique for robust FR. The suggested approach seeks to extract robust and discriminant information to reduce recognition errors. This is achieved through the optimal use of the RKPCA nonlinear projection algorithm. After that, we modified the technique to lower the dimensionality of the retrieved features using the Color LBP and Wavelet Descriptor, a suggested Color Local Binary Pattern and Wavelets transformation. Our descriptor's fundamental concept is to use a novel feature grouping technique produced by the Three-Level decomposition of Discrete Wavelet Transform (2D-DWT) and Local Binary Pattern (LBP) to determine the optimum representation of a facial picture in a discriminant vector structure. Attallah et al., [26] introduced a hand biometric system that combines knuckle and palmprint data. The Finger-Knuckle-Print and Palm-Print traits are obtained using the BSIF (Binarized Statistical Image Features) filter and LBP (Local Binary Patterns) coefficients to achieve this. The features vector is then selected using PCA (Principal Component Analysis), which transforms into higher coefficients. The Extreme Learning Machine (ELM) matches the palm-print or finger knuckle feature vector.

3. PROPOSED MODEL

The model integrates fingerprint and face identification systems and was developed for better efficiency. It has three main sections: enrolment, test, and matching.

3.1. Fingerprint Identification using DWT:

The three primary portions of the fingerprint identification system are the enrollment, test, and picture enhancement sections. Each phase contains two stages: feature extraction to extract the final practical and image enhancement. To check the system's functionality, the final elements of the test and enrollment sections are categorized using ED. Figure 1 shows the suggested fingerprint scheme.

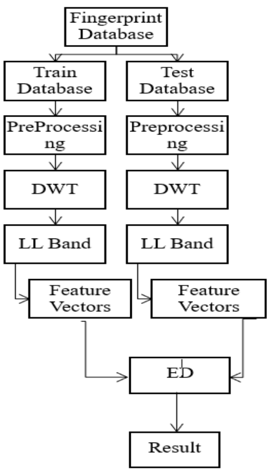

Fig. 1 Fingerprint Recognition System

3.1.1. Enrolment Section:

It has a fingerprint database, prepossessing, and feature extraction technique blocks. The preprocessing unit enhances and resizes the quality of fingerprint images [27]. The feature extraction unit uses the DWT to extract noiseless and compressed fingerprint image features.

(i) Fingerprint database

The FVC 2004 fingerprint database is the third International Fingerprint Verification Competition database [28] after FVC2000 [29] and FVC2002 [30]. The four sub-datasets of FVC2004 are DB1, DB2, DB3, and DB4, and they were gathered utilizing various sensors.

Fingerprint DB1 database

It contains eight photos of ten different people and 80 grayscale photographs in TIF format. Cross Match's optical sensor module V300 was used to collect it. Each fingerprint image in the database is 640x480 pixels. Figures 2 and 3 display the initial fingerprint images of ten distinct individuals and eight photographs of a single person for DB1.

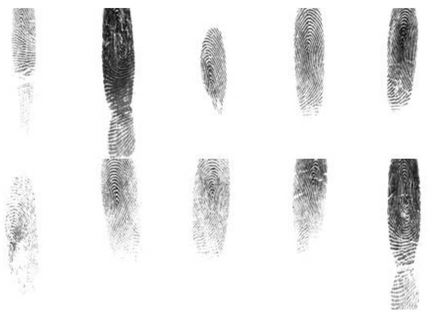

Fig 2. The initial picture of ten people for DB1

Fig 3. All eight images of the first person for DB1

- ## Fingerprint DB2 database:

Eight separate photos of ten different people are included, along with 80 grayscale photographs in TIF format. It was gathered through an optical sensor module. The size of each fingerprint image in the database is 328 x 364. Figures 4 and 5 display eight fingerprints of a person for DB2 and the initial fingerprint images of ten distinct people.

Fig 4. First fingerprints of ten persons for DB2

Fig 5. All eight images of the first person for DB2

- **Fingerprint DB3 database:**

It contains eight photos of 10 different people and 80 grayscale photographs in TIF format. Finger Chip FCD4B14CB, Atmel's thermal sweeping sensor module, was used to gather it. Every fingerprint picture in the database has dimensions of 300 by 480 pixels. Figures 6 and 7 display the initial fingerprint images of ten distinct individuals and eight photographs of a single person for DB3.

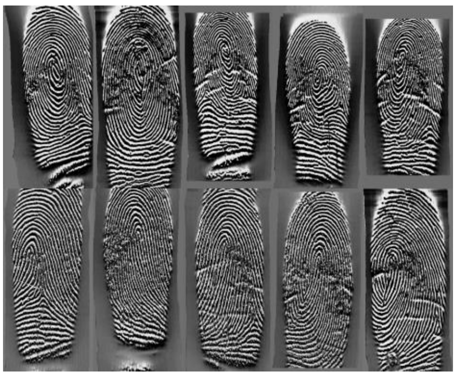

Fig 6. The first fingerprints of ten persons for DB3

Fig 7. All eight fingerprints of the first person for DB3

- ## Fingerprint DB4 database:

Eight separate photos of ten different people are included, along with 80 grayscale photographs in TIF format. Synthetic fingerprint generation ersion3.0 was used to gather it. Every fingerprint image in the database has dimensions of 288 by 384 pixels. Figures 8 and 9 display eight photos of a person for DB4 and the initial fingerprint images of ten distinct people.

Fig 8. The first fingerprint of ten persons for DB4

Fig 9. All eight images of the first person for DB4

(ii) Train database:

The fingerprint images of different persons are considered, and a database is created.

(iii) Preprocessing:

It is scaled after cropping the fingerprint image and using HE to improve contrast.

- **Crop Fingerprint Image:** As illustrated in Figure 10, the fingerprint portion of the original 640x480 fingerprint image is considered and cropped to yield only a 202x435 fingerprint size for additional processing.

(a) Original fingerprint of Size 640x480 (b) Cropped fingerprint of size 202x435

Fig 10. Fingerprint cropping

- **Histogram Equalization (HE):** Effective dispersion out of the most frequent intensity values expands the image's intensity range and improves contrast for improved viewing. Figure 11 displays the HE pictures of the original and cropped photos, along with the matching histograms.

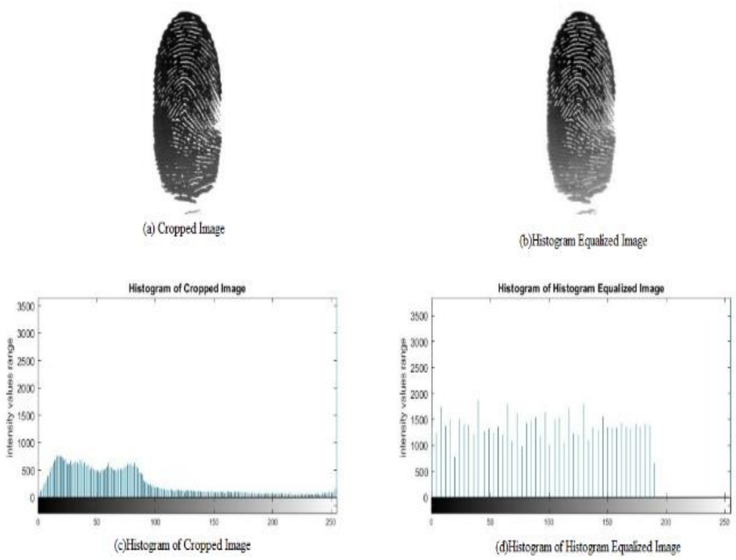

Fig 11. Histogram Equalization on the cropped image (202x435)

- **Resize of fingerprint image:** Figure 12 illustrates how the histogram equalized cropped image of 202x435 is taken into consideration and scaled to 400x400.

(a) HE image (b) Resized fingerprint images(400x400)

Fig 12. The HE Fingerprint image is resized

(iv) Feature Extraction using Discrete Wavelet Transform (DWT):

It is applied to a resized HE fingerprint image. To obtain frequency and time domain information at the same time, the transformation is discretely sampled. As illustrated in Figure 13, it decomposes the image into four sub-band images [31, 32] in order to minimize noise and compress the fingerprint image dimension by taking into account the LL sub-band of DWT with size 200x200.

(v) Feature Vectors

The LL is considered for the final features, the LL band of size 200x200 is converted into a vector of size 40000.

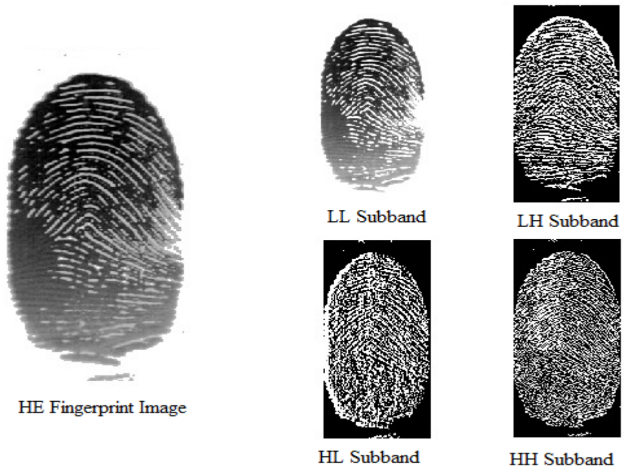

Figure 13. DWT on resized HE image

3.1.2. Matching Section:

The Euclidean distance is used in the matching section to compare the fingerprint features of the enrolment and test sections to identify human beings. This distance measures the straight-line distance between two points of two feature vectors as given in Equation 1.

$$ED = \sqrt{\sum_{i=1}^{N}(D_i - T_i)^2} \qquad \text{-------------(1)}$$

Where,

N= No. of features in the row vector

D_i= the vector containing the database features

T_i = vector containing the test features

3.1.2. Test Section:

The fingerprint pictures are evaluated for human identification in the test portion. The process used in this section is identical to that used in the enrollment section.

3.2. Face Recognition using Double Density Dual Tree DWT

The face recognition technique incorporates the idea of modified power law transformation (MPLT) to improve image quality for efficient person identification. MPLT improves the face quality after the Viola-Jones algorithm is used to identify the face region in the face images. DDDTDWT extracts the traits for efficient person recognition [33].

3.2.1 Face Databases

(i) Near Infrared Region (NIR) database

It includes pictures of 120 people's faces taken in different lighting conditions, with different scales and levels of fuzziness. Each topic has 15 photos with varying expressions, each measuring 768 × 576 pixels. A total of 1800 JPEG-formatted photos featuring 15 distinct subject expressions were taken and are as shown in Figure 14 [34].

Fig 14 A few examples of the NIR dataset's face images

(ii) YALE Database:

There is a specific amount of YALE confrontation data in the database. Eleven of the fifteen individuals they shot were captured in distinctive poses. Each participant's frontal, upright photographs were taken against a uniformly white background. The picture files are grouped using the JPEG format. Each image is 320 x 243 pixels in size, with 320 pixels for width and 243 pixels for height. These exterior appearances or designs include bright focus, joyous, light-colored, light-left, light-right, normal, miserable, sluggish, shocked, and wink. Figure 15 shows pictures of the face of a man.

Fig 15 Face image Sample of six persons of the YALE dataset [35]

(iii) Extended YALE database:

It contains 2,414 frontal-face photos, each with a pixel size of 192 x 168, an average of roughly 64 images per 38 people. The images were taken with various facial expressions and lighting conditions [36, 37]. Figure 16 displays the sample images.

Fig 16 The sample images of the Extended Yale database

(iv) ORL Database

It was collected between 1992 and 1994 and is sometimes called the Olivetti Research Laboratory (ORL) face database. It contains 40 different subjects, each represented by 10 images. Photographs of certain individuals were taken at different times, with minor changes in lighting, facial features (glasses or not), and facial emotions (smiling or not).

The subjects of each image were placed in front of a uniformly dark background, upright, with considerable leeway to move to the side. Images in the PGM format are 92 x 112 in size. Figure 17 shows samples of database images [38].

Fig 17 Samples of ORL Database

3.2.2 Face Detection using Viola Jones Algorithm

Face identification performs poorly when face photos of the same subject are shot in settings with varying lighting, backdrops, and alignments. To address this issue, the Viola and Jones algorithm recognizes only a picture's face region [39]. The algorithm has three steps: (i) Integral image, an image representation method for fast feature computing for the detector. (ii) Highly effective classifiers are produced using the AdaBoost algorithm, which chooses important visual characteristics from a bigger collection. (iii) cascade classifier, which uses more processing time on areas that show promise as objects and help quickly remove background areas from the image. Using a Haar basis feature filter, gradients of pixel intensities with specific orientations are used to detect and extract face features, such as the location and size of the eyes, mouth, and nose bridge. Features of the Haar basis function include the following three categories: (i) two rectangular features, which determine the variation in the total values of the pixels in the two rectangular areas. The sum of the pixel values in the central rectangle is subtracted from the sum of the pixel values in the two outer rectangles to determine the three rectangle features (ii). The difference between the total of pixels in diagonal pairs of rectangles is calculated by the four-rectangles feature (iii). The ability to use the rectangle's four corner values to calculate the sum of all pixel values inside the rectangles is made possible by the integral image. The integral image is produced by adding all of the numbers above and to the left of a specific value. The AdaBoost algorithm, a machine learning technique that searches for relevant and irrelevant features before eliminating irrelevant ones, handles the problem of only a small number of the numerous available features, being important for face detection. The pertinent traits are subsequently weighted to identify a face within a specified window. P (a feature's ability to identify a face in a collection of face photos) > 0.5 indicates that the feature is meaningful if it outperforms random guessing. The Adaboost algorithm then uses a linear combination of the weak classifiers, as shown in Equation 2, to create a strong classifier. These pertinent attributes are weak classifiers.

$$F(x) = a_1 f_1(x) + a_2 f_2(x) + a_3 f_3(x) + \ldots \text{-----------------}(2)$$

Where a_n is

$$\begin{cases} 0, & \text{if feature performs less than random guessing.} \\ 1, & \text{if feature performs better than random guessing.} \end{cases}$$

The photos typically contain more non-face regions and fewer faces. However, the Viola-Jones algorithm frequently searches for faces in photos of varying sizes. Therefore, they must be thrown out immediately to obtain the desired outcome in a short amount of time. Due to the longer computation time, a single strong classifier is insufficient. As a result, a series of weak classifiers is employed, each of which has distinct characteristics. In each step, the sub-windows—a small portion of an image with specific dimensions—are checked to see if they contain a face. If they do not, the sub-windows are rejected. A sub-window must have a face if it makes it through every step and the face is identified.

3.2.3 Image Enhancement with Modified Power Law Transform (MPLT)

The method introduces a novel approach, MPLT, to address the problem of low exposure and poor contrast in face images. Power law transformations (PLT) are used to change the pixel's intensity value, and they are given in equation (3).

$$O = c\, I^{\gamma} \quad \text{-------------------}(3)$$

Where,

O and I are the pixel values of output and input images.

c is a constant operator,

γ is variable for γ<1, the output image brightness is enhanced, whereas γ>1 makes the image darker.

Om Prakash Verma et al. [40] presented two separate PLT operators, the intensity or Value component and saturation component, as given in equations (4) and (5), to enhance the image's exposure.

$$V' = \lambda\, V^{\beta} \quad \text{---------------------}(4)$$

Where,

V is the original Value or intensity

V' is the transformed Value

β<1 constant

λ is the intensity constant

$$S' = \sigma\, S^{\alpha} \quad \text{--------------------}(5)$$

Where,

S is the original saturation,

S' is the transformed saturation,

σ is the saturation constant,

α is a constant > 1,

The Value and Saturation components presented by Om Prakash Verma et al., are modified in the method [33] to enhance the quality of the image further using equations (6) and (7),

$$V_{new} = \phi \, V^{log_{10}(e+\beta)} \text{ ----------(6)}$$

Where,

V_{new} is the new transformed value.

V is the original value or intensity.

ϕ is the constant

β is a constant < 1

e is the exponential constant with value 2.7182 (e=2.7182).

The $\log_{10}$ is used in the above equation as it produces small changes for relatively large changes in the values of β. Hence, the proposed method provides good control over the pixel values, which influence the quality and appearance of the image.

$$S_{new} = \psi \, S^{(e-\alpha)} \text{ -------------------(7)}$$

Where,

S_{new} is the transformed saturation,

S is the original saturation,

ψ is the saturation constant,

α is constant

e is the exponential constant with value 2.7182 (e=2.7182).

The exponential constant *e* provides a flexible range of values for the Saturation component and thus provides good control over the saturation component of the image. The quality of an image is measured with function exposure, which denotes the number of gray levels of images that are highly under-exposed and is given in equation (8),

$$Exposure = \frac{1}{L} \times \frac{\sum_{x=1}^{L} h(x) \times x}{\sum_{x=1}^{L} h(x)} \text{ --------(8)}$$

Where,

x = Gray level value of the image,

$h(x)$ = Histogram of the image,

L = Total no. of gray levels (Normalized in the range [0,1]).

Exposure is a function used to estimate the illumination level of an image based on its histogram and gray levels. The pixel intensity value of the histogram of correctly exposed images is fairly centered in mid-range and distributed on all intensity levels, whereas the histogram is skewed to one side for poorly exposed images. The enhancement of images through the MPLT method preserves the naturality and enhances the quality of the image, thus providing a visually pleasing image.

3.2.4. Feature Extraction using Double Density Dual Tree Complex Discrete Wavelet Transform (DDDTCDWT).

DDDTDWT is a technique that efficiently identifies a person by extracting features [41] from detected and augmented facial photos. This method alters the default DWT by using two oversampled DWT concatenations—that is, combining Dual Tree DWT and double-density DWT. This includes both Dual Tree DWT and Double Density DWT characteristics. Each of these methods offers benefits and traits of its own. Shift-invariance is almost achieved by the Dual-Tree Complex Wavelet Transform (DTCWT) [42].

It features a wavelet transform with Gabor-like complex-valued wavelets, produced by parallelizing the real and imaginary components of a complex transform using two DWT filter banks. In this case, the upper portion of DWT is interpreted as the real component and the bottom portion as the imaginary part by means of filters. Wavelets associated with upper DWT are the approximate Hilbert transform of wavelets associated with lower DWT for a given set of filters. When used for tasks like picture denoising and augmentation, DTCWT performs better than the critically sampled DWT. Other characteristics include direction selectivity at higher dimensions.

Double Density Discrete Wavelet Transform (DD DWT) [43] is based on two wavelets and a single scaling function. The two wavelets are intended to be half offset from each other; the integer translates of one wavelet falling in the middle of the other wavelet's integer. Among its significant benefits is that it is two times more complete. It is almost shift-invariant. Complex wavelets with real and imaginary components that approximate Hilbert pairs are suggested to reduce signal noise. DDDTDWT is constructed using four wavelets and two separate scaling functions. Two wavelets are intended to offset each other by half, forming an approximate Hilbert transform pair. One of the four wavelet pairs is intended to be offset from the other pair, with the integer translates of one wavelet pair falling halfway between those of the other pair. The two complexes, or roughly analytic wavelets, can be constructed by simultaneously designing one pair of wavelets to approximate the Hilbert transform of the other pair. Its filter bank structure comprises iterated oversampled filter banks running in parallel. Compared to DWT, dual-density DWT, dual-tree DWT, and other current noise reduction and shift invariance techniques, the feature extraction method used in the DDDTDWT method is superior. More directionality is seen in DDDTDWT than in any other windowing technology. Five subbands are produced using the fourth breakdown level in the tests. The subband that remains after the fourth level of decomposition—the low-frequency component—is considered. More traits are included in it than in the other four subbands. The fifth sub-band, or sub-band values produced after the fourth level of decomposition, are transformed into a single-column vector and then transferred into a matrix that contains the characteristics of various people in successive rows. The test features were obtained using these database features on the test image.

3.2.5. Euclidean Distance (ED).

It calculates the likelihood that a test image will match the features in the database, as indicated by equation (9). The test image is considered to match the database image if the ED value between the two images is less than the critical value. If the ED value exceeds the crucial value, the test image is not a match.

$$ED = \sqrt{\sum_{i=1}^{N}(D_i - T_i)^2} \qquad \text{-----------------------(9)}$$

Where,

N=No. of features in the row vector

D_i= a vector containing the database features

T_i = vector containing the test features

3.3. Bimodal Biometrics identification of human beings by integration of the Fingerprint and Face images

Human Recognition is based on the Fusion result scores of the fingerprint and face recognition systems using the Bayesian theorem [44] in Equation 10.

$$F(S_1, S_2) = \frac{S_1 * S_2}{(1-S_1)(1-S_2)+S_1 * S_2} \qquad \text{------------------------------- (10)}$$

Where s1 and s2 denote recognition result scores provided by fingerprint and face, respectively.

4. EXPERIMENTAL RESULTS

Experiments have been conducted to authenticate the proposed bimodal biometrics for efficient human recognition by fusion of fingerprint and face images methodology's performance scores on the MATLAB R2022a platform and compared it with existing approaches.

4.1. Performance of Fingerprint Recognition System

The three different trains and test fingerprint combinations of 7:1, 4:4, and 1:7 are considered with four Fingerprint databases: DB1, DB2, DB3, and DB4. The Percentage Recognition Rate (PRR) is given in Table 1. The PRR increases as the number of fingerprint images increases in training. The PRR values are better for DB3 and DB4 as the images are visible clearly.

Table 1:- The PRR values for various combinations of train and test Fingerprint images

Fingerprints	Train and Test combinations		
	7:1	4:4	1:7
DB1_B	88	65	51
DB2_B	89	70	60
DB3_B	99	91	72
DB4_B	94	81	69

Table 2 gives the average PRR for various combinations of train and test fingerprints of DB1 to DB4. The average PRR values are better for DB3 and DB4.

Table 2:- Average PRR for various combinations of train and test databases

Fingerprints	Average PRR
DB1-B	68
DB2-B	73
DB3-B	87.33
DB4-B	81.33

The fingerprints are mixed from DB1 to DB4 to obtain a Hybrid Fingerprint Database, which combines the best visible and non-clear fingerprints. Table 3 gives the average PRR results for train and test combinations of 4:4.

Table 3: PRR value for Hybrid Fingerprint database

Hybrid Fingerprint Database	Average PRR
	77.5

4.2. Performance of Face Recognition System

Table 4 gives the average Percentage Recognition Rate (PRR) for different combinations of PID and POD with various face databases. The ORL database's face images are very clear, so the average PRR is as high as 99. The Extended YALE Database Average PRR is as low as 92.75 since the face images are unclear.

Table 4: The Average PRR for four face databases

Face Databases	Average PRR
NIR Face Database	95.75
YALE-B Database	97.50
Extended YALE Database	92.75
ORL Database	99

The four face database images are mixed to obtain a Hybrid face Database, which combines the best visible and unclear face images. The Average PRR results are given in Table 5.

Table 5: The average PRR values with Hybrid Face Database

Hybrid Face Database	Average PRR
	96.5

4.3. Performance of Bimodal Biometrics System

The Recognition of human beings is based on the Fusion of the fingerprint and face recognition system's average PRR scores using the Bayesian theorem.

$$F(S_1, S_2) = \frac{S_1 * S_2}{(1 - S_1)(1 - S_2) + S_1 * S_2}$$

Where,

S_1=Fingerprint recognition systems average PRR value

S_2=Face recognition systems average PRR value

$$F(77.5, 96.5) = \frac{77.5 * 96.5}{(100 - 77.5)(100 - 96.5) + 77.5 * 96.5}$$

Average PRR with fusion technique = 98.96%

4.4. Performance Comparison of Unimodal and Proposed Bimodal Biometric Systems

As Table 6 shows, the performance of the bimodal biometric system with a combination of fingerprint and face is better than that of the unimodal biometric system.

Table 6: Comparison of Unimodal and Bimodal Biometric Systems

Biometric Systems	Average PRR
Unimodal Fingerprint Biometrics System	77.50
Unimodal Face Biometrics System	96.50
Bimodal Biometric System	98.96

The advantages of the proposed Bimodal biometrics are as follows

(i) It combines two different biometric modalities like fingerprint and facial recognition,

(ii) Enhanced Accuracy by Combining two biometric modalities reduces the chances of false acceptances and rejections, improving overall system accuracy.

(iii) Improved Security by requiring two forms of identification, bimodal biometrics makes it harder for unauthorized users to gain access. This dual-layer protection helps mitigate risks like spoofing or hacking.

(iv) Increased in Reliability as different biometric traits can serve as backups for each other. If one modality fails (e.g., a wet fingerprint), the system can still authenticate a user through the second modality (e.g., facial recognition).
(v) Robustness in Varied Conditions in different biometric traits performs better under different environmental conditions like lighting, dirt, etc. Bimodal systems can adapt to these variances, ensuring reliable performance.
(vi) Reduced Risk of Identity Theft using two modalities decreases the likelihood of identity fraud, as attackers need to replicate both biometric traits.
(vii) Bimodal biometrics generally outperform single-modal systems regarding overall performance and security.

5. CONCLUSION

The integration of two distinct biometric characteristics, fingerprints, and facial recognition, is necessary for effective person recognition utilizing bimodal biometrics to improve security and accuracy. This research suggests using fingerprint and facial photos for efficient person recognition based on bimodal biometric traits. After cropping the fingerprint portion of an image, HE is applied. DWT transforms the spatial domain into a transform domain with low and high-frequency bands after the cropped HE image has been enlarged to 400 x 400. The high-frequency bands of LH, HL, and HH are eliminated to reduce noise and dimensionality in the low-frequency LL-band of size 200 x 200. The LL band coefficients are transformed into column vectors for the final features. To calculate performance metrics, test fingerprints, and database fingerprints are compared using the ED. A modified power law transform and the Viola-Jones algorithm are the foundations of facial recognition. The DDDTDWT accomplishes feature extraction. To calculate performance parameters, the ED compares the features gathered from the database, and tests face photos. The Bayesian theorem combines the calculated Percentage Recognition Rate (PRR) for fingerprint and face recognition systems. The suggested method's recognition rate is higher than that of unimodal biometrics.

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