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Precise Face Recognition through GWO-Cuckoo Optimized Neural Networks and MRMR Feature Selection from Compressed Hybrid Domain Fusion

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Abstract: In the domain of computer vision, face recognition systems play a pivotal role, particularly in the context of security and access control. This research paper introduces a novel approach to face recognition that leverages the fusion of compressed hybrid domain grades at a matching level. It takes into consideration two distinct compressed hybrid domain algorithms, referred to as algorithm one and algorithm two, with the aim of enhancing accuracy across ORL, YALE, and JAFFE face databases. In algorithm one, a combination of histogram intensities, discrete wavelet transform (DWT), and double density dual tree discrete wavelet transform (DDDTDWT) is employed for feature extraction. Notably, this algorithm also segments the binary bits of image pixel decimal values into most significant bits (MSB) and least significant bits (LSB). DWT is subsequently applied to the MSB, while the histogram of oriented gradients (HOG) is used for the LSB matrices. Meanwhile, Algorithm two explores a distinct approach by utilizing the GIST descriptor concept on the LL-sub band of DWT and HOG features, which are later combined through convolution. Moreover, for the neural network classifier, a GWO-Cuckoo optimized architecture is employed, ensuring that the extracted features are optimally utilized for precise face recognition. In addition, the minimum redundancy maximum relevance (MRMR) feature selection method is integrated into the feature extraction process. This further enhances the discriminative power of the selected features. The results achieved through this proposed technique are highly promising. Specifically, for the ORL, YALE, and JAFFE databases, accuracy rates of 97.71%, 100%, and 100% are achieved, respectively, surpassing the performance of existing methods.

Keywords: Biometrics, DDDTDWT, DWT, Face recognition, Fusion, GIST, Histogram, HOG.

1. Introduction

Human identity based on conventional methods like a physical key, identity card, smart card, secret password, personal identity number (PIN) [1], and so forth., is not reliable, for the reason that portable gadgets used may be misplaced or stolen, maybe forgotten, quickly expected or maybe cracked via faux assaults. Biometrics have been given much attention, and alternative methods to conventional methods have become the most reliable option for human popularity.

Biometrics denotes the involuntary identity of humans primarily based on their physiological and behavioral traits [2], which, intern relies upon on capabilities of human body elements and the conduct of a human being corresponding. The face recognition system has been extensively used in every phase of life with low-cost computation systems that have moulded a massive consideration to automatically handle face images for various applications, including inquiry, human-computer interaction, biometric validation, and multimedia management. Face identification offers many advantages over other biometrics methods, such as mobile phones and surveillance cameras that take pictures at a distance. A system designed to identify or confirm a human being from a video frame or image is involved in face recognition.

The challenges of human recognition based on face images are the variations in face images due to age factors [3], resolution [4], facial expressions [5], poses [6], and lighting conditions [7] which outcome in face recognition systems' low performance.

Problem definition: In the domain of computer vision, face recognition systems have emerged as a critical technology, particularly in the context of security and access control. Conventional methods of human identification, such as physical keys, identity cards, and PINs, have proven to be unreliable due to issues like loss, theft, forgetfulness, and susceptibility to unauthorized access. Biometrics, which relies on the unique physiological and behavioral traits of individuals, has gained significant attention as a more dependable alternative. Among various biometric methods, face recognition stands out as a versatile and cost-effective solution for applications such as inquiry, human-computer interaction, biometric validation, and multimedia management. However, the effectiveness of face recognition systems is challenged by the inherent variations in face images caused by factors like age, resolution, facial expressions, poses, and lighting conditions. These challenges have led to a need for innovative approaches that can enhance the performance and accuracy of face recognition. The problem addressed in this research is to develop a novel approach to face recognition that overcomes the limitations of existing methods. Specifically, the goal is to improve the accuracy of face recognition by introducing a fusion of two distinct compressed hybrid domain algorithms.

Contribution: The two algorithms' results are fused at matching levels. Algorithm one uses Histogram, DWT, and DDDTDWT for features. Algorithm two uses the concept of binary segmentation of every pixel, and DWT, HOG, and GIST techniques are used for features. The accuracy result of the proposed method is better than the two individual algorithm results.

Organization: The research paper is systematically organized as follows: the literature survey on existing face recognition approaches is pronounced in section 2. The background required for the projected model is given in section 3, the proposed algorithm is specified in section 4, and section 5 offerings a result assessment. Section 6 contains the conclusion of the research.

2. Literature survey

Present methods of human recognition based on face images are discussed. The current pre-processing techniques, extracting features, and classifications to compare features of the face recognition process using different techniques are presented.

A method for face identification based on canonical correlation analysis was proposed by Nhat and Hoang [8] that involves concatenating dissimilar features to code a facial image. Block partition is used to inspect the extraction of facial structures using the methods LBP, HOG, and GIST. Nguyen-Quoc and Hoang [9] suggested combining HOG and GIST descriptors to extract features from facial images. Two groups of features are combined into a single feature set by the canonical correlation examination. To remove unconnected and distorted features, the Fisher ranking is considered. Shadi M. S. Hillies and Huda Mady [10] suggested enhancing the recognition of faces that supported video transmission under entirely different creation, facial expressions, light variation, occlusion, orientation, movement, and position disparity. Viola-Jones' algorithmic rule was utilized to improve the identification of the face. Face features were extracted using a combination of LBP and HOG (histograms of orthogonal gradients). The methods used in face organization are SVM and RF. Jyothi Ravikumar et al. [11] proposed a convolutional extraction system for facial authentication using DWT and HOG. A compressed number of transform domain LL band coefficients is obtained by applying the DWT to face images. The HOG is applied on the LL band for additional compression with LL coefficients to find oriented gradients. The ultimate features are gained by convolving LL with HOG coefficients. Fahima Tabassum et al., [12] The coherence of DWT is combined with four different algorithms: an error vector of principal component analysis (PCA), an eigenvector of PCA, an eigenvector of linear discriminant analysis (LDA) and convolutional neural network (CNN) then a combination of four results are done using the entropy of detection probability and fuzzy system. X. Guo et al. [13] reviewed the literature on facial expression recognition based on machine learning, which included image preprocessing, feature extraction, and image classification. The advantages and limitations of various facial expression recognition methods are compared. Mohammed and Al-Alawy [14] proposed the DWT-HOG-based face recognition system. The DTW technique is used first to extract the frequency content and provide the sub-bands for each selected

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face image. The HOG technique is then applied to each sub-band to extract the valuable features.

Monisha et al. [15] proposed facial identification based on 2D-DWT feature extraction and a qualified significant wavelet tree to get the correct yield while compressing the face images. The convolution neural network (CNN) is used for classification. Alobaidi and Mikhael [16] proposed a sparse face-recognition depiction method that utilizes the L2 rule. Two non-orthogonal approaches, DCT and DWT, are combined or used separately to create face identification schemes. The weight-based SRFI scheme is fused with selected factors from the DCT and DWT fields. Ravinaik et al. [17] introduced modified power law transform using double density dual tree discrete wavelet transforms (DDDTDWT) to extract features for face recognition. The Euclidian distance (ED) compares database features and tests face images to compute performance parameters. Richa Srivastava et al., [18] presented an implementation of Dual tree complex wavelet transform (DTCWT) and DDDTCWT executed in VLSI architecture. The transform techniques are applied to image processing to exploit merits and demerits.

Gamal Fahmy et al., [19] presented two Bivariate denoising of image approaches based on double density discrete wavelet transform (DD DWT) and double density dual tree complex wavelet transform (DD CWT). Both techniques decomposed noisy images with either DD DWT or DD CWT decompositions and then applied the Bivariate denoising technique for noise removal.

The authors of [31] introduces an enhanced approach for human face recognition, employing a back-propagation neural network (BPNN) and novel feature extraction methods based on image correlations. The potential drawback lies in the limited exploration of the approach's performance on more extensive and diverse datasets, which is critical for assessing its real-world applicability.

The authors of [32] presented a novel face recognition algorithm that combines multi-level histogram sequence center-symmetric local binary pattern (M-HCSLBP) with Fisherface to address the challenges of high dimension and computational complexity in feature extraction. The proposed approach achieves the highest recognition rate and exceptional robustness, as demonstrated through experiments on ORL, Yale, and GT face databases. One potential drawback of the M-HCSLBP method is that it may require significant computational resources, which can limit its efficiency when dealing with large-scale datasets or real-time applications.

In [33], the authors enhance sparse representation for small sample face recognition using a transfer learning method with labeled samples and a weighted fusion scheme, resulting in high accuracy rates (95% on ORL and FERET datasets and 83.33% on LFW). However, a drawback is their reliance on the availability and quality of labeled data, which could pose challenges in certain scenarios.

In [34], the authors propose a novel deep learning network, CSGF(2D)^2 PCANet, to tackle issues like data redundancy, computation time, and rotation invariance in face recognition. The method enhances feature extraction through 2-D PCA, binary hashing, blockwise histograms, and linear SVM for output. However, it lacks detailed discussion on computational complexity and resource requirements, potentially impacting its efficiency, especially with large datasets in practical applications.

In [35], the authors present a novel face recognition algorithm that combines global and local Gaussian-Hermite moments (GHMs) to enhance feature extraction in corrupted face images, delivering superior accuracy, particularly in the presence of salt and pepper noise. However, a potential drawback is the limited discussion on the method's computational complexity and resource demands, which could influence its practical efficiency, particularly in real-time or large-scale applications.

In [36], the authors introduce a novel facial feature extraction method that combines interpolation-based directional wavelet transform (DIWT) and local binary patterns (LBP) to enhance local feature robustness for face image variations. However, a potential drawback lies in the limited discussion about the method's computational complexity and scalability, which can be crucial for real-time applications and handling large-scale datasets.

In [37], the authors proposed a face recognition model that combines the windowing technique, DCT, average covariance, and ANN, resulting in improved recognition rates with fewer features and reduced computational complexity. However, the limited discussion of its robustness to lighting, pose, and expression variations is a potential drawback, potentially impacting real-world performance in diverse environments.

The authors in [38] presented a sparse batch normalization convolution neural network model for facial expression recognition, tackling gradient and overfitting problems. However, a drawback is the limited evaluation on datasets other than JAFFE and CK+, raising concerns about the model's performance in diverse datasets and real-world scenarios.

The hybrid emotion recognition approach presented in [39] combines geometric and appearance-based features with a multi-class Support Vector Machine. However, a drawback is the potential limitation in handling a broader range of nuanced emotional expressions, which may restrict its applicability in real-world contexts requiring more fine-grained emotion recognition.

Drawbacks of each conventional technique mentioned in the literature review:

1. Canonical correlation analysis (CCA) with LBP, HOG, and GIST (Nhat and Hoang [8]): CCA, which concatenates dissimilar features, may result in high computational complexity. Furthermore, it might not effectively handle variations in lighting, poses, and facial expressions. The use of LBP, HOG, and GIST features can introduce significant computational overhead without a clear explanation of their fusion, making it challenging to understand their collective impact on recognition accuracy.
2. HOG and GIST descriptor combination (Nguyen-Quoc and Hoang [9]): While combining HOG and GIST descriptors is a promising approach, the paper lacks detailed information regarding the specific methodology used for feature fusion. It is crucial to provide a clear explanation of how the combination addresses challenges such as occlusion and variations in facial expressions to enhance transparency and comprehensibility.
3. Viola-Jones algorithm with LBP and HOG features (Shadi M.S. Hillies and Huda Mady [10]): The Viola-Jones algorithm is a popular choice for face detection, but it may not robustly handle variations in facial expressions and illumination, potentially leading to suboptimal recognition performance. Additionally, the combination of LBP and HOG features, known for its computational intensity, may require efficient dimensionality reduction techniques to maintain computational efficiency and accuracy.
4. DWT and HOG feature combination (Jyothi Ravikumar et al. [11]): The DWT-HOG approach offers powerful feature extraction, but it may suffer from issues related to high dimensionality, which can affect computational efficiency and necessitate feature selection or reduction methods. A more detailed explanation of how dimensionality challenges are addressed is essential for a comprehensive understanding.
5. Sparse face recognition using DCT and DWT (Alobaidi and Mikhael [16]): Combining DCT and DWT for face recognition introduces complexities in feature selection and fusion. The paper should provide a clear rationale for choosing between these two orthogonal approaches and clarify the effectiveness of the weight-based SRFI scheme in combining selected features. Without this information, it is challenging to assess the advantages of this approach over other methods.
6. Modified power law transform with DDDT-DWT (Ravinaik et al. [17]): While the modified power law transform with DDDT-DWT is a promising approach, the paper lacks a detailed discussion of the specific challenges it addresses. The methodology for comparing database features and testing face images using Euclidean distance should be elaborated to understand how this approach improves recognition accuracy.
7. Dual tree complex wavelet transform (DTCWT and DDDTCWT) (Richa Srivastava et al. [18]): While DTCWT and DDDTCWT are efficient for image processing, their implementation in VLSI architecture may encounter limitations, such as hardware constraints and real-time processing challenges. The paper should provide a more comprehensive discussion of these potential drawbacks to emphasize the uniqueness of the proposed research.
8. Bivariate denoising with DD DWT and DD CWT (Gamal Fahmy et al. [19]): The paper lacks a clear discussion of how bivariate denoising addresses the challenges in face recognition. Without a detailed explanation of the drawbacks and limitations of the conventional techniques, it is challenging to appreciate the novelty and advantages of the proposed research. Clarifying these drawbacks is essential for positioning the research effectively.

This research paper distinguishes itself from existing literature by introducing a unique approach that combines two distinct compressed hybrid domain algorithms (algorithm one and algorithm two) with innovative feature extraction techniques,

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Figure. 1 ORL face image samples of one person [20]

Figure. 2 YALE face image samples [21]

Figure. 3 JAFFE database samples [22]

including segmentation of binary bits and novel combinations of DWT, HOG, and GIST features. It further differentiates by optimizing the neural network classifier through a GWO-Cuckoo architecture and integrating the MRMR feature selection method, resulting in highly promising accuracy rates for face recognition across the ORL, YALE, and JAFFE databases. These novel elements collectively position this work as an innovative and superior solution in the realm of face recognition, addressing the limitations of conventional methods and offering remarkable accuracy.

3. Background

3.1 Face databases [20]

The publicly available benchmark face databases, viz., ORL, YALE, and JAFFE, are used to examine the projected method. The model's overall performance is tested by considering the diverse samples in the face picture databases.

3.1.1. ORL database

Face images captured between 1992 and 1994 are included in the olivetti research laboratory (ORL)'s standard face database. Forty individuals were photographed in ten facial expressions, such as open/closed eyes, smiling/not smiling, with/without glasses, and varying lighting conditions. The face images were taken on a dark background with upright and frontal positions. The photos are in PGM format, and each image has a size of 92×119. Ten image samples of a single person are displayed in Fig. 1.

3.1.2 YALE database

The collection consists of 165 grayscale images with a GIF format of 15 people and 11 samples per person. Each image displays various facial expressions, including happy, sad, normal, sleepy, surprised, wink, with glasses, without glasses, center-light, left-light, and right-light. Fig. 2 shows the individual samples.

3.1.3 Japanese female face expression (JAFFE)

It has ten distinct people and 20 images for each person totalling 200 sample images. The images with a size of 256×256 grayscale. The face images were taken in an upright and frontal position. Fig. 3 shows the images of a single person, which are in JPG format.

3.2 Discrete wavelet transform (DWT)

This process involves breaking down a signal into four separate bands through filters [23]. This transformation is achieved by combining high pass and low pass filters, which are then sampled by a factor of 2 to create four sub-band images. Each process level results in one approximation (LL) image and three detailed bands (LH, HL, and HH) corresponding to vertical, horizontal, and diagonal details shown in Fig. 4. While the LL band contains significant information from the original image, the other bands have insignificant information, such as edge details shown in the first part of Fig. 4 (b).

The initial transformed domain features are taken from the LL band coefficients, while the three detailed bands are discarded due to their insignificance. This results in a reduction in the number of features and an increase in the speed of computation through compression.

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(a) (b)

Figure. 4 DWT of an image: (a) Original image and (b) DWT Image of Original image

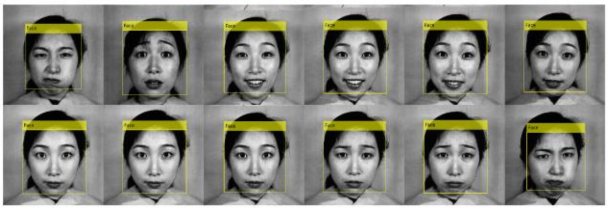

Figure. 5 The Detected face part by the Viola-Jones algorithm [23]

3.3 Double density dual tree discrete wavelet transform (DDDTDWT)

De-noising is accomplished using the transformation, which is shift invariant and performs significantly better than critically sampled DWT. It possesses the traits of dual-tree DWT and double-density DWT. The double-density dual-tree DWT [24] has the same parallel operation of two oversampled iterated filter banks as the dual-tree DWT. For image de-noising, picture quality enhancement, segmentation, motion estimation, and compensation, the DDDTDWT is employed. The coefficients of the fifth sub-band are regarded as characteristics. With a compression ratio of 16:1, the DDDTDWT is applied to a face image with dimensions of 240×320 and is regarded as the sixth band of sizes of 4800.

3.4 Face detection

The face part is cropped in the digital images using the Viola-Jones algorithm [25]. It is better for faces with frontal views than angled ones. It notices the face part with the nose, eyes, and mouth, as shown in Fig. 5, and the detected face image is resized to 80×80.

3.5 GIST descriptor

It is the condensed data technique that Olive and Torralba proposed [26]. The output of the GIST descriptor is low-dimensional data that comprises adequate evidence to recognize the required part in the images. It emphasizes the parts in the figure, which is a relation between the outline of the region and its assets. It neglects the limited objects in the image and their connotations. The genuineness, directness, unevenness, extension, and roughness are expressive human remarks and denote the spatial building of the image.

The calculation procedure of the universal GIST descriptor is finding the spatial, frequency, and orientations. The 32 Gabor filters from 4 scales and eight directions are convolved with the face image to yield the 32 feature maps of a similar size to the original image. The image is separated into 4×4 grids with 16 regions; the average feature values within every area are computed. The total number of concluding features is 16 regions, and 32 features per region to get 512 features.

3.6 Histogram of oriented gradients (HOG)

It is the process of counting histograms of gradient directions in local areas of face images [27]. The magnitudes of gradient values are high around edges and corners as more information about the object shape than the flat region. The magnitude and direction of every pixel value compute the gradients. The image matrix of size 80×80 is segmented into several 16×16 blocks; each block comprises four cells of size 8X8 pixels. The HOGs for each cell are calculated and dispersed into nine histogram bins which vary between 0 to 180 degrees angles, and the range of each bin is 200. A bin is nominated for each pixel based on the direction and the corresponding magnitude values. The four adjacent cells of 8x8 are clustered into one block of size 16×16 and have 9×4 = 36 HOG constants. The final HOG features of the image are attained by using the 50% overlap of every block. The overlapped blocks in an LSB matrix are 9×9=81, and the number of HOG features is 81×36 = 2916.

3.7 Artificial neural network classifier

It is built on the biological neural networks found in humanoid brains. It consists of three unrelated layers: the input layer comprises only one layer and is responsible for taking the input data [28]. It takes the final features as inputs, executes the computations via its neurons, and the data is moved onto the succeeding hidden layers. The middle layer between the input and the output layers is the hidden layer in multiple numbers. The output layer collects the data from the hidden layer and moves outside the network. The numeral of nodes in the output layer is equal to the required outputs.

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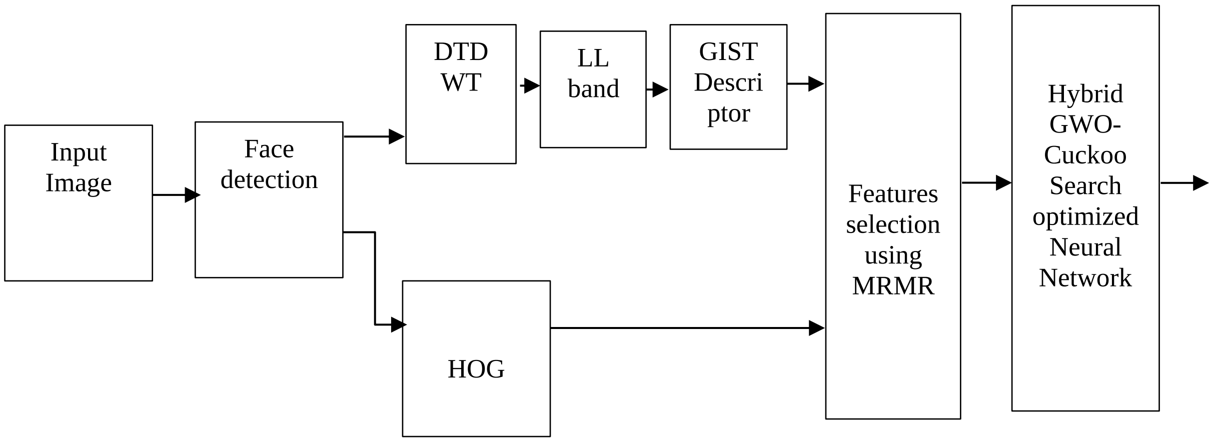

Figure. 6 Proposed method for face recognition

Table 1. Proposed system using matching level fusion algorithm

Input: The face image databases viz., ORL, YALE, and JAFFEE were used to inspect the expected method. Output: The accuracy of the proposed system is computed. 1. The accuracy of the face recognition algorithm one is computed, resulting in R1. 2. The accuracy of the face recognition algorithm two is computed, resulting in R 2. 3. The accuracy of the proposed model is computed by the fusion of R1 and R2 at the matching level with the following Equation: $\text{Accuracy} = \text{Mean of R1 and R2} \times \frac{\text{Max of R1 or R2}}{\text{Min of R1 or R2}}$ 4. Final results are improved compared to the individual results.

4. Proposed algorithm

Problem Definition: The person recognition system is developed by fusing the outcomes of two algorithms at the matching level, as given in Table 1.

Objectives: Human beings are identified competently using a proposed system based on combinations of two algorithms with succeeding purposes.

- To explore effective feature extracting using spatial and transform domain techniques to recognize a person effectively.
- To increase the recognition accuracy of the system.
- To ascertain whether the proposed method's results are better than the existing methods.

4.1 Compressed hybrid domain face recognition algorithm 1

The compressed algorithm 1 [29], which is presented in Table 2, provides information on human recognition based on compact histogram, discrete wavelet transform (DWT), and double density dual tree discrete wavelet transform (DDDTDWT) using Face images under uncontrolled conditions. histogram intensities, DWT, and DDDTDWT, three sets of features, are computed. Histogram extracts the first set of features; only 200 out of 256 are considered prominent. Using DWT, the second set of features is recovered, and when only approximating LL band coefficients are taken into account, the number of features is only 1/4th of the original size, which was 120×160 = 19200. Fifth-level band coefficients are regarded as features and have a dimension of 4800 in the third set of features derived using DDDTDWT. Concatenating the three features, which are robust and compressed with sizes of 24200, yields the final features. To calculate the recognition accuracy performance metric, Euclidian distance (ED) is used to associate the database and the test face picture features.

4.2 Compressed hybrid domain face recognition algorithm 2

This efficient compressed hybrid domain features face recognition using face detection, binary segmentation of pixels, DWT, Histogram of Gradients (HOG), and GIST descriptor [30] is given in Table 3. The benchmarked face image databases were resized to 112×92. The Viola Johnes algorithm is used for the face part detection and resized to 80×80, then converted image pixel decimal values into 8-bit binary. The binary bits are segmented into most significant bits (MSB) and least significant bits

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Table 2. Compressed hybrid domain face recognition algorithm 1

Input: Face images from benchmarked databases. Output: Accuracy of identification is computed. 1. The regular databases of face images viz., ORL, YALE, and JAFFEE are used to inspect the expected method. 2. The different-sized face images from various databases are shrunk to the same size of 240×320, and color photographs are converted into grayscale versions. 3. Applying the histogram to a face image with a size of 240×320=76800 yields 256-dimensional histogram coefficients. Only 200 key values are taken into account in the first batch. 4. Face images are analyzed using DWT, and the first level LL band of size 120×160=19200 is considered to be the second set of initial features. 5. DDDTDWT is applied to face images and considered the third set of initial features in the dimension of 4800. 6. The final feature, 24200, is attained by concatenating Histogram coefficients, LL band coefficient, and DDDTDWT fifth band coefficients. 7. The compression ratio of final features is 68.49% 8. To examine the proposed model, the distance formula ED is used between the face images of the database and test images. 9. The model's accuracy is computed to obtain the result R1.

Table 3. Compressed hybrid domain face recognition algorithm 2

Input: Benchmarked Face image databases. Output: Accuracy of identification is computed. 1. The regular ORL, YALE, and JAFFEE face image databases were used to examine the expected technique. 2. Color images are converted into grayscale images, and dissimilar-sized images are resized to a uniform 112×92 size from different databases. 3. Face detection using the Viola-Jones algorithm is performed and detected face images are resized to 80×80. 4. Every pixel's decimal value is converted into binary and segmented into most significant bits (MSB) and least significant bits (LSB) 5. The images are reconstructed from MSB and LSB with a size of 80×80. 6. The DWT is used on the MSB image and considered LL band coefficient matrix of size 40x40. 7. The GIST Descriptor is used on the LL band matrix, resulting in 640 coefficients. 8. HOG is applied on LSB image results in 2916 coefficients. 9. The 640 GIST descriptor coefficients and 2916 coefficients of HOG are convolved to get the final 3555 features. 10. The artificial neural network classifier examines the proposed model. 11. The model's accuracy is computed to attain the result R2.

(LSB) and converted each 4-bit binary into corresponding decimal values, then reshaped into the matrix of size 80×80. The DWT and HOG are used on MSB and the LSB matrices. The GIST descriptor concept is applied to the LL-sub band of DWT to extract the first set of initial features and HOG features as the second set of features. The final compelling features are attained using the convolution of GIST and HOG features. The artificial neural network (ANN) is used to classify the features of face image databases and test images to verify the system's performance.

4.3 Feature selection using minimum redundancy maximum relevance (MRMR)

The MRMR technique for feature selection strives to identify pertinent features closely associated with the target variable, while simultaneously diminishing redundancy among the chosen features. The mathematical representation of MRMR is outlined as follows:

Consider:

- X as the collection of features ($X = \{X_1, X_2, X_3, ..., X_n\}$).
- Y as the target variable.

The objective entails identifying a subset of features S^* that maximizes the correlation with the target variable Y and minimizes duplications amongthe selected features within the subset. This objective can be formulated as an optimization challenge:

$$Maximize: I(X_i, Y) - \sum\left[I\left(X_i, X_j\right)\right] \quad (1)$$

Where $X_i \in S^*$ and $X_j \in S^*$, $i \neq j$

In this context, $I\left(X_i, X_j\right)$ denotes the mutual information between feature X_i and the target variable Y , while $\sum\left[I\left(X_i, X_j\right)\right]$ signifies the cumulative mutual information among all pairs of features X_i and X_j within the subset S^*.

The principal aim of the MRMR feature selection method is to determine the subset S^* that maximizes the optimization objective. This endeavour entails striking a balance between the significance of features concerning the target variable and the minimization of overlap within the selected features. The outcome is a subset of features that substantially contribute to the classification task without unnecessary redundancy.

MRMR holds significant utility in machine learning and data analysis, as it enhances model performance and reduces computational complexity. The mathematical formulation of MRMR is captured as follows:

Let X denote the set of all features, and Y denote the target variable (class labels).

1. Evaluate the relevance of each feature in relation to the target variable Y . This assessment can be conducted using relevant measures such as mutual information, correlation, or other appropriate metrics. Let $I(X_i, Y)$ symbolize the relevance of feature X_i concerning Y.
2. Calculate the redundancy between pairs of features. For each pair of features $\left(X_i, X_j\right)$, calculate the mutual information or another suitable measure that quantifies how similar or redundant these features are. Let $I\left(X_i, X_j\right)$ represent the redundancy between features X_i and X_j.
3. Calculate the MRMR score for each feature X_i using the formula:

$$MRMR(X_i) = \frac{I(X_i, Y)}{\left(\frac{1}{|X|} \sum\left[I\left(X_i, X_j\right)\right]\right)} \tag{2}$$

   Where $|X|$ is the total number of features, Σ denotes the sum over all pairs of features $\left(X_i, X_j\right)$, and $I(X_i, Y)$ is the relevance of feature X_i to the target variable.
4. Arrange the features according to their MRMR scores in a descending sequence opt for the highest MRMR score's top-k features to proceed with additional analysis or model creation.

The MRMR technique endeavours to identify a subset of features that, as a whole, offer the utmost pertinent information for the target variable, concurrently reducing duplication among the features. This serves to enhance the efficiency and efficacy of machine learning models, particularly in contexts involving high-dimensional data or an extensive array of features.

Following are the relationship with MRMR for feature selection:

- GIST Descriptor coefficients: This feature is denoted as X_1. It captures textural information from face images.
- HOG Features: These features are denoted as X_2 . Face features capture texture pattern variations in the face.

Now, let's define the relation of these features with MRMR for feature selection:

- X represents the set of all features available for selection: $X = \{X_1, X_2, \}$.
- Y represents the target variable, such as face class labels.
- S represents the subset of features selected by MRMR.

For a specific feature X_i, the mutual information between X_i and the target variable Y is denoted as $I(X_i; Y)$. It quantifies how much information about the target variable is carried by feature X_i.

Similarly, the mutual information between two features X_i and X_j is denoted as $I\left(X_i; X_j\right)$. It measures the redundancy between these features.

The MRMR objective function is defined as:

$$MRMR(S) = \frac{1}{|S|} \sum_{X_i \in S} I(X_i; Y) - \frac{1}{|S|^2} \sum_{X_i, X_j \in S} I(X_i; X_j) \tag{3}$$

The goal of MRMR is to find the subset S of features that maximizes the relevance to the target variable $\left(I(X_i; Y)\right)$ while minimizing the redundancy between selected features $\left(I\left(X_i; X_j\right)\right)$.

In this context, the MRMR algorithm would select a subset of features from X (which includes X_1, X_2, X_3, X_4) that collectively provides the most informative and non-redundant information for the classification of face detection.

4.4 GWO-Cuckoo optimized NN classifier

4.4.1. Objective function

The objective function that needs to be minimized is related to the error or loss in the training of an artificial neural network (ANN). In this paper, the mean square error (MSE) is used.

The mean square error measures the average squared difference between the predicted outputs and the actual outputs for a set of training patterns.

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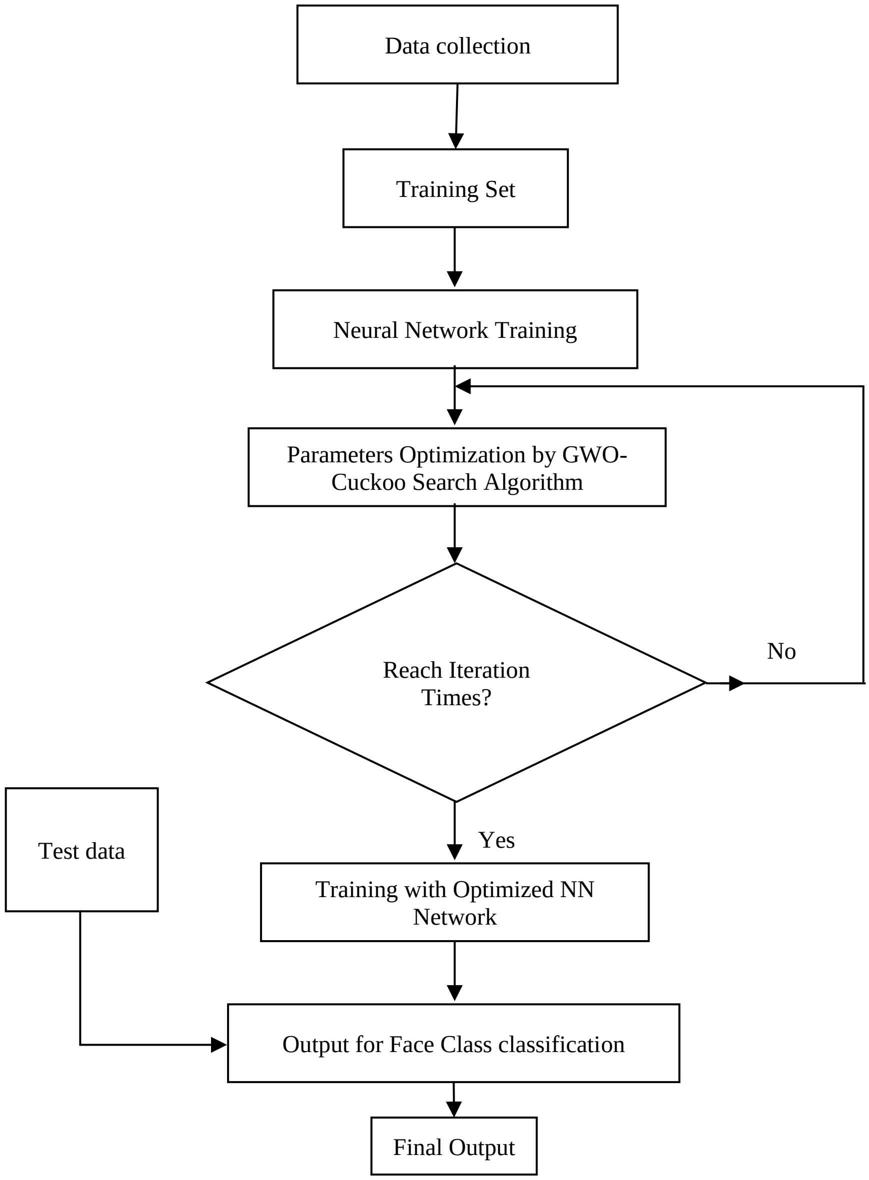

Figure. 7 Flow diagram for optimized model based on Neural Network and GWO-Cuckoo Search approach

$$\hat{w} = \min_{w \in \mathbb{R}^d} f(w, X) \tag{4}$$

$$f(w, X) = \frac{\sum_{i=1}^{|X|} (\hat{y}_l - y_i)^2}{|X|} \tag{5}$$

Where:

- w is the weight vector of the ANN.
- X is the set of training patterns.
- $\hat{y}_l$ is the expected output for pattern x_i.
- y_i is the actual output for pattern x_i.
- $|X|$ is the number of training patterns.

4.4.2. Hybrid grey wolf-cuckoo search initialization

Populations for grey wolves optimization (GWO) and Cuckoo search are initialized. The population size, maximum number of iterations, and other relevant parameters for both algorithms are defined. The GWO population is denoted as G, and the Cuckoo search population is denoted as C.

4.4.3. Hybrid optimization iterations

Iterations are performed where GWO and Cuckoo search are executed concurrently or sequentially. In each iteration:

GWO Phase:

1. Solutions (parameter configurations) are generated using GWO, resulting in a set of potential weight vectors $\{w_1, w_2, \ldots, w_N\}$ where N is the population size.
2. The fitness of each solution w_i is evaluated by computing the MSE using the objective function defined earlier.

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Table 4. Accuracy of algorithm 1

Face Databases	ORL	YALE	JAFFE
% Accuracy	97	100	100

3. The best solutions with the lowest MSE from GWO are selected. The best GWO solution is denoted as w_{best}.

Cuckoo search phase:

1. Solutions are generated using Cuckoo search, resulting in a set of potential weight vectors $\{w'_1, w'_2, \ldots, w'_M\}$ where M is the population size.
2. The fitness of each solution w'_j is evaluated by computing the MSE using the objective function.
3. The best solutions with the lowest MSE from Cuckoo search are selected. The best Cuckoo search solution is denoted as w'_{best}.

Hybrid Update:

Based on the best solutions found by GWO and Cuckoo search, the hybrid optimization process is updated. Different strategies can be employed, such as:

- Using w_{best} as the starting point for Cuckoo Search or vice versa.
- Modifying parameters, like learning rates, based on the progress of the other algorithm.

These steps are repeated for a specified number of iterations or until convergence criteria are met.

4.4.4. Training the neural network

The neural network is trained with the best weight vector obtained from the hybrid optimization process. In this case, w_{best} or w'_{best} is used, depending on which one resulted in the lower MSE.

4.4.5. Evaluation

The performance of the trained neural network is evaluated using validation data or by computing the MSE on a separate validation set to assess generalization.

4.4.6. Refinement

Based on the performance of the trained network, further refinements may be made to the hybrid optimization process. This could involve adjusting parameters such as population size, interaction strategies, or fine-tuning the hyperparameter ranges.

4.4.7. Testing

The final trained neural network is tested on an independent test set to evaluate its performance and generalization to unseen data.

4.4.8. Analysis

The results are analyzed to determine if the hybrid optimization has improved the neural network's performance in terms of minimizing the MSE. The computational cost and the trade-off between optimization performance and time are compared.

The hybrid grey wolf-cuckoo search optimization approach leverages the strengths of both algorithms to efficiently explore the weight space of the neural network and find the weights that minimize the MSE. This approach helps in improving the network's accuracy and robustness in fitting the training data and making accurate face recognition.

5. Performance evaluation

The proposed technique's performance is analyzed by computing the percentage accuracy performance parameter. The proposed method is tested with face databases ORL, YALE, and JAFFE. The percentage accuracy of the projected technique is computed by fusing two compressed hybrid domain algorithm results at the matching level.

5.1 Accuracy result of compressed hybrid domain face recognition algorithm1

(i) The total recognition rate (TRR) is the Computed number of approved individuals who successfully matched the predefined database using Eq. (6).

$$\mathrm{TRR} = \frac{\text{No. of authorized persons correctly matched} \times 100}{\text{Total no. of persons in the database}} \tag{6}$$

(ii) The false rejection ratio (FRR) counts authorized persons who have been rejected as unauthorized.

(iii) False acceptance rate (FAR) counts unauthorized persons who have been accepted as authorized persons.

(iv) The equal error rate (EER) refers to the point at which FAR and FRR values are equal at a specific threshold. A value of EER results from a compromise between a value of FRR and a value of FAR. Having a lower value of EER increases the algorithm's performance.

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The percentage accuracy is computed with the ORL face database with the persons inside database (PID) and persons inside database (PID) ratio of 10:30, the YALE face database with the PID and PID ratio of 5:5, and the JAFFE face database with the PID and PID ratio of 5:5. The computed Percentage Accuracy is presented in Table 4. The percentage accuracy of the JAFFE is higher than ORL and YALE face databases because the dissimilarities in face images are less with JAFFE.

5.2 Accuracy result of compressed hybrid domain face recognition algorithm 2

The Percentage Accuracy is calculated with the ORL, YALE, and JAFFE face databases using a train and test face image ratio of 60:40 in the ANN classifier specified in Table 5. The overall accuracy is higher in the ORL and JAFFE face databases, as face images have very few dissimilarities.

5.3 Accuracy result of the proposed fusion-based face recognition algorithm

The accuracy values of compressed hybrid domain face recognition Algorithms 1 and 2 are fused at a matching level to obtain better results in the proposed algorithm. The accuracy of the proposed algorithm is computed by the fusion of R1 and R2 accuracies of compressed hybrid domain face recognition Algorithms 1 and 2 at the matching level using the ORL, YALE, and JAFFE face databases with Eqs. (7-13).

$$Accuracy = \text{Mean of R1 and R2} \times \frac{\text{Max of R1 or R2}}{\text{Min of R1 or R2}} \quad (7)$$

The correction term is included in the Percentage accuracy calculation if the result attains a value of more than 100, then rounded off to 100 to regulate the final Percentage accuracy.

$$\text{Mean of R1 and R2 with ORL face database} = \frac{97+95.5}{2} = 96.65 \quad (8)$$

$$\text{Percentage Accuracy with ORL face database} = 96.25 \times \frac{97}{95.55} = 97.71 \quad (9)$$

$$\text{Mean of R1 and R2 with YALE face database} = \frac{100+91.33}{2} = 95.67 \quad (10)$$

$$\text{Percentage Accuracy with YALE face database} = 95.67 \times \frac{100}{91.33} = 100 \quad (11)$$

Table 5. Accuracy of Algorithm 2

Face Databases	ORL	YALE	JAFFE
% Accuracy	95.5	91.33	98

Table 6. Proposed method comparison with Algorithms 1 and 2

Face Databases	Percentage Accuracies		
	Algorithm 1	Algorithm 2	Proposed Fusion Method
ORL	97	95.5	97.71
YALE	100	91.33	100
JAFFE	100	98	100

Table 7. Proposed method comparison with existing methods on the ORL face database

S. No	Authors and year	Techniques	Percentage Accuracy
1	Abuzneid and A. Mahmood [31], 2018	LBPH+Multi-KNN	97.5
2	Xu et al., [32], 2017	Fish (PCA+LDA)	97.2
3	Liu et al., [33], 2019	Sparse Representation and Extended Transfer Learning	95
4	Kong et al., [34], 2018	Circular symmetrical Gabor filter $(2D)^2$PCA neural networks	97.50
5	Song et al., [35], 2019	fusion of global and local Gaussian-Hermite moments	97.50
6	Mohd. Abdul Muqeet and Raghunath S. Holambe, [36] 2019	interpolation-based directional wavelet transform and LBP	97
7	Proposed Method	Fusion Technique at a matching level	97.71

$$\text{Mean of R1 and R2 with JAFFE face database} = \frac{100+98}{2} = 99 \quad (12)$$

$$\text{Percentage Accuracy with JAFFE face database} = 99 \times \frac{100}{98} = 100 \quad (13)$$

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5.4 Comparison of proposed fusion face recognition method with compressed hybrid face recognition algorithms 1 and 2

The proposed fusion method at the matching level accuracy values is equated with compressed hybrid face recognition algorithms 1 and 2 in Table 6. It is noticed that the proposed method's accuracy is better than the individual compressed hybrid face recognition algorithms 1 and 2.

5.5 Comparison of the proposed fusion face recognition method with the existing methods on the orl face database

The percentage accuracy of the proposed fusion technique is compared with existing ORL face database techniques and is presented in Table 7. The Proposed technique's Percentage accuracy is improved than the current techniques presented by Abuzneid and A. Mahmood [31], Xu et al., [32], Liu et al., [33], Kong et al., [34], Song et al., [35], Mohd. Abdul Muqeet, and Raghunath S. Holambe, [36].

Table 7 offers a comprehensive comparison of the proposed face recognition method with existing techniques using the ORL face database. The existing methods are noteworthy in their own right, with Abuzneid and A. Mahmood [31] achieving a high accuracy of 97.5% using LBPH combined with Multi-KNN. Similarly, Xu et al. [32] utilized the FISH method (PCA+LDA) and achieved an accuracy of 97.2%. While these techniques demonstrate strong performance, the proposed method, a Fusion Technique at a matching level, outperforms them with an impressive accuracy of 97.71%. This superior performance can be attributed to the fusion technique's effectiveness in combining the strengths of different feature extraction methods, resulting in a more robust and discriminative feature set. By integrating various complementary feature extraction methods, the proposed technique can capture a wider range of facial characteristics, making it well-suited for handling the inherent complexity and variability in facial expressions. This comprehensive and versatile approach is the theoretical reason behind the proposed method's superior accuracy compared to existing techniques in the context of the ORL face database.

5.6 Comparison of the proposed fusion face recognition method with the current approaches on the YALE face database

The percentage accuracy of the proposed fusion technique is related to the current techniques with the YALE face database and is presented in Table 8. The Proposed technique's Percentage accuracy is improved than the current techniques presented by Abuzneid and A. Mahmood [31] and Divya et al., [37].

Table 8. Proposed method comparison with existing methods on the YALE face database

S. No.	Authors and Years	Techniques	Percentage Accuracy
1	Abuzneid and A. Mahmood [31], 2018	LBPH + Multi - KNN	96.7
2	Divya et al., [37], 2020	The windowing technique uses DCT, average covariance, and ANN.	98.89
3	Proposed Method	Fusion Technique at a matching level	100

Table 8 presents a comparative analysis of the proposed face recognition method with existing techniques using the YALE face database. Notably, Abuzneid and A. Mahmood [31] achieved a solid accuracy of 96.7% using LBPH combined with Multi-KNN, while Divya et al. [37] utilized the windowing technique involving DCT, average covariance, and ANN to achieve an even higher accuracy of 98.89%. However, the proposed method, a Fusion Technique at a matching level, surpasses all with a perfect accuracy of 100%. The theoretical reason for this superiority lies in the unique strength of the fusion technique to integrate multiple feature extraction methods, which enhances the diversity and richness of the feature set. The fusion technique's adaptability to capture different aspects of facial information and fuse them effectively results in a highly discriminative feature set that excels in recognizing faces even under challenging conditions. This versatility and capability to handle complex facial variations make the proposed method the standout performer among existing techniques in the context of the YALE face database.

5.7 Comparison of the proposed fusion face recognition method with the current approaches on the JAFEE face database

The percentage accuracy of the proposed fusion technique is related to the current techniques with the JAFFE face database and is presented in Table 9. The Percentage accuracy is healthier than the current techniques presented by Cai et al., [38], and Yaddaden et al., [39].

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Table 9. Proposed method comparison with existing methods on the JAFFE face database

S. No.	Authors and Year	Techniques	Percentage Accuracy
1	Cai et al., [38], 2018	Sparse batch Normalization CNN	95.24
2	Yaddaden et al., [39], 2018	combine geometric-based from facial fiducial points and appearance based from Discrete Wavelet Transform coefficients for features	96.19
3	Proposed Method	Fusion Technique at a matching level	100

Table 9 provides a comprehensive comparison of the proposed method with existing techniques on the JAFFE face database. Cai et al. [38] achieved an accuracy of 95.24% using sparse batch normalization CNN, while Yaddaden et al. [39] used a combination of geometric-based features from facial fiducial points and appearance-based features from discrete wavelet transform coefficients to attain an accuracy of 96.19%. However, the proposed method, employing a fusion technique at a matching level, stands out with a perfect accuracy of 100%. The superiority of the proposed method can be attributed to its unique fusion technique, which effectively combines information from multiple sources, enhancing the diversity and richness of the feature set. The fusion technique's adaptability to capture various aspects of facial information and consolidate them into a highly discriminative feature set contributes to its remarkable accuracy. It excels in recognizing facial expressions even in challenging conditions, showcasing its theoretical robustness and ability to handle complex variations in facial expressions, making it the most promising approach for the JAFFE face database.

6. Conclusion

This paper presented a novel approach to enhance the accuracy of face recognition. The proposed method combines two compressed hybrid domain algorithms at a matching level to achieve improved results. In the first algorithm, a combination of histogram intensities, discrete wavelet transform (DWT), and double density dual tree discrete wavelet transform (DDDTDWT) was employed for feature extraction. In the second algorithm, pixel decimal values were segmented into most significant bits (MSB) and least significant bits (LSB), with DWT applied to MSB and histogram of oriented gradients (HOG) used for LSB feature extraction. Additionally, the GIST descriptor concept was applied to the LL-sub band of DWT to extract an additional set of initial features. The final features resulted from the convolution of GIST and HOG features. Empirical results, as demonstrated through comparisons with existing approaches, distinctly highlight the enhanced performance of the proposed method across multiple face databases. Notably, the method achieved an accuracy rate of 97.71% on the ORL database, surpassing the performance of existing techniques, and further excelled with 100% accuracy rates on the YALE and JAFFE databases. This substantial improvement underscores the scientific contribution of this work, offering a more precise and effective solution for face recognition applications in various domains.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

M. Shanmugam, the principal author, was responsible for conceiving and designing the study, overseeing experimental procedures, conducting data analysis, and composing the manuscript. He adeptly executed data acquisition and analysis, generated graphical representations, and made significant contributions to manuscript development. His active involvement in the study design provided invaluable insights during data interpretation, and he meticulously revised the manuscript. V. M. Viswanatha and K. B. Raja served as project supervisors, each contributing critical assessments of the manuscript, with V. M. Viswanatha serving as the research supervisor and K. B. Raja as the co-supervisor.

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