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Entropy-Efficient Image Enhancement Using Twicing Functions for Makeup-Affected Face Recognition in Low-Light Conditions

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ABSTRACT

Face Recognition (FR) under non-uniform illumination and with makeup-influenced images remains a significant challenge due to substantial variations in color and brightness. This study proposes an entropy-efficient image enhancement method to improve facial image recognition accuracy in such scenarios. A hybrid fusion approach for Face Image Enhancement (FIE) is introduced, focusing on contrast optimization and visual improvement. The enhancement process operates exclusively on the L component in the CIE-Lab color space, ensuring contrast improvement while preserving overall color consistency. A novel modified order-adaptive Twicing function is employed to achieve an entropy-efficient enhancement of local direct current (DC) coefficients in the compressed discrete cosine transform (DCT) domain. Enhanced features are extracted for both query and template images using a Local Binary Pattern (LBP)-based method, facilitating precise template matching through correlation analysis. The proposed approach is evaluated on multiple datasets, including the Yahoo Makeup Face, Yale, AR, and ORL databases. Comparative analyses are conducted using various image enhancement techniques, with signal-to-noise ratio (SNR), entropy, and absolute standard deviation (SD) difference evaluated during the FIE phase. Precision and recall metrics are further employed at the FR phase. The results demonstrate consistent performance improvements, with precision ranging from 86.2% to 93.1% and recall ranging from 92.7% to 100%, depending on dataset size and complexity. These findings highlight the system's robustness in enhancing FR accuracy under challenging lighting conditions and with makeup-altered datasets. The proposed FIE-FR (face image enhancement-face recognition) system provides a novel, entropy-efficient framework that bridges the gap between image enhancement and accurate FR.

1. INTRODUCTION

It is possible to enhance and simultaneously detect faces within images under low-light conditions by employing color contrast enhancement (CCE) approaches. However, FR systems face significant challenges as detection efficacy degrades under non-uniform illumination and the presence of makeup. In FR systems, FIE serves as a crucial preprocessing step, essential for improving the system's overall robustness and accuracy. The importance of FIE lies in its ability to generate high-quality facial images, enabling the identification of distinctive attributes that better capture unique facial features. The motivation to integrate cutting-edge methods from various studies lies in the potential to effectively enhance low-light makeup-affected photographs for FR. To address issues such as noise, incorrect color representation, and insufficient contrast, deep learning (DL) models, such as DC coefficient scaling (DCCS) proposed by Alam et al. [1] and the entropy-based model developed have demonstrated significant improvements in image quality. Approaches to color image enhancement are generally classified into two categories: transformation-based techniques and spatially-based techniques. DCT [1] and Discrete Wavelet Transform (DWT) are commonly used in image enhancement applications. Alam et al. [1] proposed an approach to improve the contrast of color images and compared the performance of the CLAHE method with that of DCCS in the compressed DCT domain. Furthermore, an alternative version of image enhancement was developed in the CIE-Lab color space, where only the L component is enhanced to improve contrast, while preserving the color information in the a and b components. This leads to higher entropy in traditional methods. In addition to the SNR and disorder, the actual mean difference is another metric used to compare performance. Entropy and SNR are assessed for various enhancement approaches, and concluded that CLAHE improves SNR for images with uneven lighting, whereas LAB-DCT is more effective for maintaining true color in images. However, the LAB-DCT method is sensitive to variations in mean brightness (MB). Table 1 represents list of the numerous abbreviations used in the manuscript.

Zhuang and Guan [2] have proposed a sub-histogram approach based on an entropy adaptation process to improve contrast. Versaci presented an efficient entropy-adaptive local sub-histogram-based contrast enhancement method. This approach divides the histogram of the input image into four groups based on its entropy value and adjusts the contrast range of each sub-histogram accordingly. Performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and normalized relationships are employed. However, this method has limitations, as it can distort edges or objects, resulting in halo artifacts when there is a large contrast difference, making it less suitable for FR tasks. Additionally, focusing on statistical distributions rather than individual pixel values, spatial entropy loss can enhance the learning process, resulting in images with higher perceived quality. Moreover, incorporating fusion techniques, such as the algorithm proposed, which integrates tasks for contrast enhancement and visibility restoration, can further guide the enhancement process. By combining these approaches, a comprehensive strategy can be developed to optimize low-light makeup images, improving accuracy and performance in FR. A reliable and effective enhancement framework that integrates contrast enhancement methodologies with optimization techniques can significantly advance FR tasks in challenging conditions.

Table 1. List of abbreviations used in the paper

Abbreviation	Description	Abbreviation	Description
DCT	Discrete Cosine Transform	CCE	Color Contrast Enhancement
DWT	Discrete Wavelet Transform	LTP	Local Ternary-Patterns
FIE	Facial Image Enhancement	LBP	Local Binary-Patterns
FR	Face Recognition	CLAHE	Contrast limiting adapting histogram equalization
IE	Image Enhancement	LBP	Local Binary Pattern
SDE	Spatial Domains Enhancements	SNR	Signal to Noise Ratio
DCCS	DC coefficient scaling	SVD	Singular Value Decomposition
HE	Histogram Equalization	SWT	Stationary Wavelets Transforms
AHE	Adaptive Histogram Equalization	UWT	Un-decimated Wavelet Transform)

The goal of this work is to develop an effective makeup FIE method to improve the performance of FR systems. The ultimate objective is to establish an entropy-efficient FIE method capable of preserving facial characteristics and mitigating color distortions while enhancing FR accuracy. Employing entropy-efficient techniques is critical for optimizing an image's information content, ensuring the retention of textures, edges, and fine details that are often compromised during image degradation. Additionally, entropy-based methods improve visual contrast and dynamic range, facilitating better human perception of details.

A two-pass entropy-efficient FIE approach is proposed, utilizing adaptive augmentation of the DC coefficient in the DCT domain. In the first pass, the image enhancement process is optimized, while the second pass evaluates the effectiveness of the FR technique through template matching. The visible color shifts in facial makeup images present significant challenges for contrast enhancement and the FR phase. Mustafa et al. [3] compared image enhancement techniques based on DCT and DWT. The article provides a comprehensive analysis of these methods and offers recommendations for future image enhancement techniques. The research shows that the proposed image enhancement methodology, which combines DWT, Singular Value Decomposition (SVD), and DCT, offers improved efficiency and flexibility. While the DWT-SVD approach outperforms existing methods, it is sensitive to noise, and the threshold values used for SVD can significantly impact the results. To improve the matching efficiency of feature sets within the FR system, unique wavelet fusion and morphological processing techniques are integrated. Previous studies have explored a range of methods for enhancing image quality Vishwakarma and Mishra [4], with contrast enhancement being one of the most widely adopted approaches. According to Anish Kumar the primary challenge with high-quality images, such as those from digital cameras and HDTVs, lies in image augmentation. Various factors, such as energy, environmental conditions, and the devices used to capture the image, can easily alter image quality, often resulting in image degradation. Consequently, a wide range of image enhancement techniques have been developed to restore the content of such images. Their research provides an overview of several color image enhancement approaches, including contrast adjustment, histogram equalization (HE) and its improved variations, Homomorphic filtering, Retinex, and wavelet multi-scale transforms.

Contrast enhancement focuses on improving the perceptible distinction between adjacent visual colors, particularly in low-light face images. Advanced FR design stages often incorporate efficient techniques for contrast augmentation to address these challenges. Furthermore, achieving visual aesthetics that appeal to viewers is a critical consideration in such enhancements.

The analysis of these methods helps identify the most promising approach for future research. Aswathy Mohan [5] emphasized that image enhancement improves the brightness of low-contrast images, such as those from satellites and CT scans. In their work, a novel hybrid method was proposed based on transforms like DWT, DCT, and SVD. The method involves dividing the image into blocks, restoring the singular value matrix, and then transforming each block into the DWT-SVD-DCT domain. The components are then combined, and the updated image is generated using inverse DCT and DWT. This approach employs adaptive histogram equalization (AHE). However, AHE has the potential to amplify noise, particularly in areas with low image activity. Chaitanya et al. [6] proposed a more reliable copyright control strategy. In their method, the color image is split into three color channels (RGB), with the blue channel (B) being subjected to DWT and DCT transforms. The watermark image is also divided into R, G, and B channels, with each channel undergoing a unique application of DCT. The R, G, and B channels of the watermark image are integrated into the pre-selected mid-frequency values of the B channel. Performance metrics such as Mean Squared Error (MSE), PSNR, standardized correlation, and Normalized Correlation (NC) are used to assess the effectiveness of the proposed algorithm. Hybrid transformation methods have been proposed by researchers such as Aswathy Mohan [5] and Chaitanya et al. [6] and while spatial domain enhancement (SDE) methods, such as the Contrast Limited Adaptive Histogram Equalization (CLAHE) developed by Tiwari and Patel [7] introduced a novel image enhancement approach by merging CLAHE with DCCS. They suggest using the LAB color space instead of the conventional

Y-Cb-Cr color system to improve color contrast while preserving color information in the L component. Their method enhances contrast and reduces color shifting, but CLAHE still has the potential to amplify noise in low-activity regions of the image.

DCT-based techniques are frequently employed to enhance color images, with increasing the DC coefficient in the compressed DCT domain being a common strategy. Scaling the DC coefficient can significantly improve visual contrast, but excessive scaling may introduce visual artifacts and must be applied judiciously. The primary aim of this study is to demonstrate the efficiency of FIE for improving FR systems. An entropy-efficient, adaptable FIE approach is developed to address the limitations of FR techniques when dealing with facial cosmetics. Local feature extraction and correlation matching are utilized to evaluate FR performance. The feature-oriented matching algorithm selects an unidentified facial image and compares it with a template facial image in the database. This process leverages features such as texture, contour, and statistical coloration-based criteria to enhance the FR algorithm's effectiveness and the overall FIE process.

Despite the availability of extensive facial image databases, two distinct datasets were chosen for this study to evaluate the accuracy of the proposed FIE method. The Yale database is particularly relevant as it provides face images under varied lighting conditions and expressions, making it widely utilized in FR research. Additionally, makeup is often associated with cultural and gender disparities, posing potential biases for FR systems. The Yahoo Makeup database, which includes images significantly altered by makeup, presents a challenging scenario for FR algorithms. Addressing these challenges through diverse makeup variations could help reduce biases and improve the robustness of FR systems.

Figure 1. Reference makeup and Yale series image database taken from the previous study [8]

The Yahoo makeup image database is utilized in this study, comprising 30 subjects categorized into 10 classes, with 3 images per class. For the Yale image database, 6 images representing 3 classes are selected, as the focus is primarily on color image enhancement. Reference images from the Yahoo Makeup database are illustrated in Figure 1(a), while four distinct images with varying facial expressions are used for evaluation across the AR, ORL, and Yale databases, as depicted in Figure 1, column 2. The structure of the paper is as follows: Section 2 addresses the challenges faced by FIE systems. Section 3 reviews existing work in the fields of FR and FIE. Section 4 outlines the proposed system's design and methodologies, including a detailed description of the modeling process utilizing the adaptive DCCS method in the compressed domain. Section 5 presents the results of feature extraction, image enhancement, and the FR system, supported by parametric studies. Finally, Section 6 concludes the findings and highlights potential directions for future research.

2. CHALLENGES OF FIE METHODS

Many strategies for improving face photos have been proposed in the literature. However, FIE remains a difficult task for the following instances:

a. Occlusions: People regularly use objects like hair, spectacles, and scarves to partially conceal their features. Motion, camera shake, and poor lighting can also distort them. These factors make it difficult to capture exact and accurate facial features.

b. Non-Uniform Illumination: Depending on their environment, faces are subjected to light in various ways. As a consequence, there can be highlights, shadows, or various skin tones. Due to illumination changes, it is difficult to extract accurate facial features, including color information.

c. Variation in Expression or Pose: Faces can be posed in a number of ways and might express a wide range of emotions. These variations of poses may affect how facial features appear, making it more difficult to identify people or use FR software generally.

d. Computation Time: Some FIE techniques might not work well for real-time applications because they need too much computational time. Despite the fact that execution time can vary depending on the needs.

e. Blocking Effect: When applying DCT-based enhancement techniques, the image may exhibit a blocking effect.

f. Aging: Age varies the face features, color, and makeup style significantly and makes the FR a difficult task.

FIE is critical for improving the accuracy of FR systems, but it presents several challenges. The implementation of sophisticated enhancement algorithms on mobile and embedded devices is particularly difficult due to their limited computational capabilities. Additionally, the level of enhancement varies across different facial images, complicating subsequent processing in FR systems. Over-enhancement can distort facial features, especially under makeup, leading to inconsistencies between the enhanced image and the original stored image.

Figure 2 illustrates various challenges encountered in FIE processes. Issues such as the presence of specks on the face, occlusion from hand gestures, and extreme facial expressions significantly impede the efficiency of both FIE and FR systems. For instance, exaggerated or harsh facial expressions can substantially reduce the effectiveness of FIE, particularly in advanced FR applications. To address these challenges, this study proposes an entropy-content-preserving FIE approach. By employing entropy learning techniques, the method ensures that critical image details such as textures and edges are retained during enhancement. The use of the LAB color space, combined with an order-adaptive system, mitigates the problem of over-enhancement. Furthermore, the integration of image fusion techniques helps preserve the visual content of facial images after enhancement, ensuring that the enhanced images remain consistent and suitable for FR tasks.

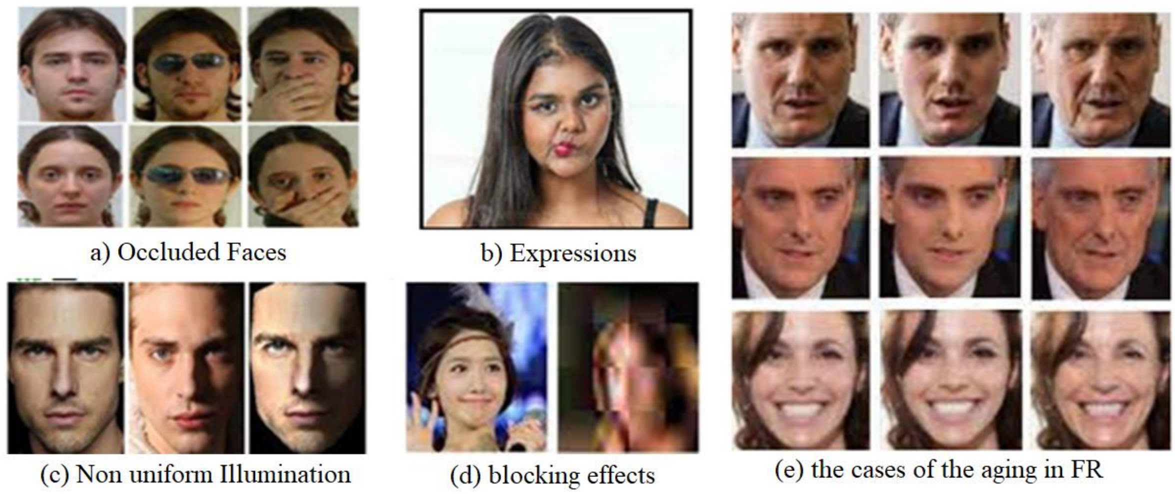


Figure 2. Representations of various challenging aspects of FIE approaches and uses in FR

3. LITERATURE REVIEW

Several approaches for image quality improvement have been proposed in various literatures, including methods that utilize the image histogram, regional enhancement, as well as transformation-based methods. This section of the study examines some of the pertinent ways for boosting true color photographs. Also, many FR approaches that have been presented in the recent past are reviewed.

3.1 Review of CCE methods

Singh and Raghuwanshi [8] proposed combining LBP-LTP and HOG features for facial makeup detection, using the FCD image dataset. They also employed additional morphological processing for enhanced feature matching. Some authors have used two face databases, abbreviated as MIW and YMU, to evaluate the effectiveness of FR systems. Eckert et al. [9] also examined FR performance using the facial FCD database. Mohamed et al. [10] utilized color image processing techniques for two encryption approaches that offer high resistance against complex forms of attacks. Their methods employ DWT and DCT in the transform domains. The required encryption keys for their proposed methods were developed using six different disorder maps with varying parameter settings. Bachhaliya and Kumar [11] proposed a contrast improvement method combined with a DWT+DCT-based image compression technique. They introduced a hybrid transform domain-based compression approach, concluding that the DWT-DCT hybrid technique, when combined with preprocessing, reduces fractional loss and offers better image quality at higher compression ratios compared to standard DWT compression methods.

Nahrawi et al. [12] aimed to provide optimal contrast enhancement for color images, addressing contrast issues and eliminating them in monochrome images to ensure accurate categorization. The problem area is normalized using a unique formula, with the SD and mean applied to both global and local image data. The resulting image focuses solely on the object (such as nuclei and cells), with a noise-free environment. The performance was evaluated using metrics like PSNR, RMSE, and mean absolute error (MAE), and the findings were compared with existing methods such as CLAHE, HE, and Grey World. The proposed method demonstrated higher PSNR and RMSE values and lower MAE values compared to the existing approaches. However, challenges persist due to inherent variations in staining intensity and cell shape. Xia et al. [13] introduced a modified multi-scale contrast enhancement (MMCE) technique to improve color images based on Twicing function-based DCCS values. This improved version of multi-contrast enhancement, called the enhanced multi-contrast enhancement (MCE), is achieved by redefining the frequency spectral bands and incorporating additional band-enhancing methods. To evaluate the performance of the technique, second-derivative measure enhancement (SDME) contrast measure, was used. Computer simulations and evaluations demonstrated that, for most images, the proposed method outperformed widely used techniques such as Retinex and the original MCE.

Jarholiya et al. [14] proposed a modified approach using DCCS in the compressed DCT domain to enhance the brightness of images while preserving the color content. They recommended scaling the DC coefficient in the CIE-Lab color space to maintain the color information, with only the L component being enhanced to improve the contrast. This method increases the entropy compared to traditional DCCS. The effectiveness of the proposed method was compared using metrics such as SNR, absolute standard deviation difference (ASDD), and probability analysis. The study also involved adjusting the order of the Twicing function for better DC coefficient expansion based on entropy analysis. Various medical images from different environments were used to test the methods. Additionally, Jarholiya et al. [14] demonstrated the successful application of image fusion techniques to further improve contrast, highlighting the advantages of pixel-based wavelet fusion. Alias and George [15] explored the use of interpolation techniques to enhance color visuals in the frequency domain. They applied DCCS for the enhancement process, which significantly improved the visual quality of the images by handling color components more effectively. The proposed strategy outperformed traditional spatial domain approaches. However, the basic DCCS method is sensitive to brightness variations, which limits its suitability for makeup face image datasets.

Hua et al. [16] developed an outdoor vision enhancement program, particularly for applications in autonomous vehicles and security surveillance, which are often negatively impacted by sand-dust rain, especially in inland regions. The study proposes an efficient method to improve images affected by sand-dust, addressing the color cast and poor contrast caused by such weather conditions. The method involves a new color balance and compensation formula to restore the color balance of the deteriorated image. Specifically, it compensates for the blue and green channel information by adding more yellow channel data, which is created when sand-dust particles bounce before the white balance adjustment. Sandeepa et al. [17] tackled the challenges of image contrast enhancement using a hybrid transform domain approach. The method combines DWT and SVD with a clipped sub-image HE approach. A filtering technique is applied, where a masking strategy is used on the low-pass filtered wavelet coefficients and their scaled versions. The scaling value is calculated using the SVD between the reconstructed approximation coefficients and a clipped sub-image HE enhanced image, which is based on the average brightness difference. However, the technique has the potential drawback of reducing visual details, particularly in the high-frequency components of the image. Mi et al. [18] addressed the common issue of low visibility in outdoor photos taken in inclement weather conditions. The study proposes an innovative method for enhancing the visibility of a single blurry input image. Their technique compensates for both the contrast and color of the image, aiming to restore the brightness and color, which are typically compromised in foggy conditions.

Zhu et al. [19] addressed the challenge of processing underwater images, which is particularly difficult due to environmental factors that often result in issues such as color cast, poor visibility, and loss of edge details. To tackle this problem, they proposed an algorithm based on light absorption-related image blurring. Their method involves using a white balance technique and color adjustment to restore the image's natural physical appearance, thus improving the overall quality of underwater images. Baranitharan and Madane [20] proposed an effective color image enhancement method based on the UWT. To preserve color information, the RGB image is first transformed into the HSI (Hue, Saturation, and Intensity) color space. The intensity component of the image is then transformed into lower and higher sub-bands through the UWT. The lower band coefficients are subsequently clustered using K-means clustering (KMC), with the number of clusters (K) being determined by the hill is ascending method. Each clustering division of the image is enhanced using logarithmic HE, thereby improving the image's contrast.

Narasimhan et al. [21] investigated the background identification of grayscale and color images, applying structural changes such as Opening by Reconstruction, the Erosion-Dilation approach, and Block Analysis. These techniques were initially applied to grayscale images, and then extended to color images by enhancing the individual color components. The compressed domain method, specifically the DCT, was employed for color image processing, contributing to improved results. Arun Kavi Arasu et al. [22] focused on analyzing various contrast enhancement methods for low-contrast images. Simulation results indicated that the proposed methods were effective in boosting contrast in low-contrast input images. The study also explored the processes, benefits, and limitations of different contrast enhancement techniques. Saleem et al. [23] proposed a contrast enhancement method that aims to avoid introducing undesirable artifacts or false appearances. They noted that global contrast-enhancement methods, while useful for improving global image content, have limited ability to enhance local features. Furthermore, these methods tend to reduce visual brightness and introduce color distortions. Local enhancement methods, on the other hand, can improve image details but may cause issues such as block breaks, noise, and artificial alterations. To address these shortcomings, the authors suggested a fusion-based contrast enhancement strategy, which combines multiple data sources to overcome the limitations of individual methods. However, the fusion approach requires multiple images and is more complex.

Nandal et al. [24] developed a method for encrypting RGB images. When RGB images are combined with grayscale images, the result often appears dark due to the accumulation of the grayscale component. To enhance the visual appeal of the image, their approach focuses on improving both brightness and contrast. The method utilizes Hue Saturation Value (HSV) and contrast enhancement to produce better color images. By separating grayscale and color information into distinct channels within the HSV color space, the method prevents contrast loss that typically occurs when images are merged in the RGB color space. This approach allows for the representation of multifunctional datasets in color images without compromising any data integrity. Zhu [25] highlighted the challenges of improving underwater images, which are affected by factors such as ocean currents, light reflection, absorption, and diffraction by suspended particles, and low light intensity. Recent techniques, including underwater image formation models and DL methods, have been used to repair underwater photos. However, these methods often result in degraded images, obscured background details, and difficulty in capturing details of the blue region borders. To address these issues, this study proposes an improved image fusion and enhancement technique, leveraging graph theory in combination with a dark channel prior.

Chiang et al. [26] Have proposed a color-encoding architecture based on the CIE-Lab color space to enhance perception and information discovery. Their approach uses large datasets to improve color comprehension and visual enhancement. By breaking down components like volume scattering, surface scattering, double bounce, and helix scatter, and projecting them into the color space, they can map the five channels obtained from this breakdown to CIE-Lab, facilitating better image understanding and distinction of the bouncing components. Sandoub et al. [27] developed a fusion-based technique for enhancing images in low-light conditions, which can be problematic in computer vision and multimedia applications. The method aims to overcome halo artifacts and color distortions caused by existing bright transmit prior and maximum color channel enhancement methods. However, their approach may still lead to color distortion, making it unsuitable for certain applications like FIE and FR. Pardhi and Thepade [28] proposed a method for improving the contrast of low-light images, which are often difficult to perceive due to poor clarity. Their approach enhances the dynamic range of these images in four steps, providing a practical solution for improving photos taken in low-light conditions. Naik and Mishra [29] focused on enhancing images to reveal more details, addressing the issue that factors such as lighting, weather, and the tools used to capture the image can easily affect its clarity. These conditions can lead to information loss and poor contrast. The goal of their enhancement methods is to uncover hidden information or improve the contrast of low-contrast images. In their work, several advanced image enhancement algorithms, including DWT, Stationary Wavelet Transform (SWT), and Un-decimated Wavelet Transform (UWT), are reviewed. Ramesh and Shanmugam [30] proposed a simpler yet more efficient image enhancement approach compared to previous methods. Unlike earlier techniques, which focus solely on the brightness component, their method handles color components and modifies the light source component, which adjusts brightness. Their results outperform many of the prior methods, demonstrating significant improvement in the spatial domain. The summary of earlier image enhancement techniques is provided in Table 2.

3.2 Review and challenges of FIE and FD methodologies

This section aims to identify various challenges of implementing the makeup face detection M-FD application for the FR task. Any makeup face detection (FD) algorithm used for FR must contend with a number of technological obstacles, which affect its reliability. There are several face mage databases readily available; the main difficulties employing these images are the variances in poses, facial expressions, dynamic image resolutions, and illumination changes.

Table 2. Summaries of the early extant image enfacement techniques and parameters

Author/Reference	Method Used	Kind of Images (Application Areas)	Used Color Spaces	Evaluation Parameters
Alam et al. [1]	DC coefficients Sculling	Contrast improvement for True color images	Used LAB space DCCS in DCT domain	MSE and PSNR histograms
Mustafa et al. [3]	Sib histogram enhancement	breaks histogram of image in four groups using entropy	RGB and Gray images	Entropy, PSNR and MSE
Aswathy Mohan [5]	DWT-SVD-DCT domain using AHE	Enhancement of satellites and CT scans images	AHE approach for the contrast enhancement in hybrid space	Histogram and MSE
Tiwari and Patel [7]	CLAHE and DCCS	Comprised DCT domain DCCS and combination to CHAE enhancement	Color RGB image and gray image enhancement	PSNR and MSE
Eckert et al. [9]	HOG and LBP features	addressed the FCD database and cosmetic images for facial recognition	Color image RGB	Quality of HOG and LBP features
Jarholiya et al. [14]	DC coefficients Sculling	Medical image enhancement via contrast scaling & fusion	LAB color space and L component is used	PSNR and MSE
Mi et al. [18]	Gradient based enhancement	Color image multi-scale gradients based enhancement	EGB colure space and gray domain	MSE
Baranitharan and Madane [20]	Contrast stretching	Enhancement in UWT	RGB space to gray converted image	PSNR
Pardhi and Thepade [28]	Dynamic Range Adjustment	Contrast Enhancement Using Adaptive Threshold Based range adjustment	LUV Color Space is adopted as modified space	Mean absolute difference MAD MSE, PSNR
Sandoub et al. [27]	Image Fusion for Contrast enhancingt	dark contrast image fusion for patch-based image enhancement	RGB color space and gray images	MB error, entropy
Our proposed work	DC coefficients Scaling in DCT and wavelet Fusion	It is proposed to adopt Twicing function order for Face image	LAB colure space L component is used for enhancement	MAD, SD MSE, PSNR, Entropy MB

Eckert et al. [9] addressed the FCD database and cosmetic images for facial recognition testing, utilizing a combination of HOG and LBP features. According to previous studies, the FCD database is considered somewhat more challenging to use compared to the MIW and YMU databases. Additionally, the Yale database, which is a gray-level database, contains various expressions and poses but does not incorporate all the challenges that other databases might cover. This highlights the complexity and diversity of challenges faced in facial recognition tasks, where no single database encompasses all potential variations.

- It is challenging to establish a FR system for the facial makeup images that accurately outperforms under illumination variations under makeup methods.
- There are numerous feature descriptors available in the literature, and the selection process is highly subjective. The currently used feature-based approaches for detecting facial cosmetics are either computationally too difficult or inefficient.
- Using the FIE algorithm may result in significant variations in local features, potentially leading to inefficient feature extraction. LBP and Histogram of

Gradients (HOG) were previously combined and used as descriptors to identify makeup photos. Since makeup is susceptible to variations in local features, a descriptor defined in local texture spaces is needed. The face markup can be found using LBP, the easiest texturing approach.

To design an efficient enhancement method for improving the performance of a FR system for makeup databases, it is essential to focus on maintaining minimal complexity in feature set extraction.

Sharif et al. [31] proposed a method for recognizing and detecting human actions, utilizing entropy and distance features for segmentation and action recognition. García-Montero et al. [32] introduced a hand gesture estimation algorithm that employs Hough forest and skin detection methods, with a filter for tracking hand movements. However, the Hough forest approach is computationally intensive and struggles with deformation. Hussain et al. [33] proposed a local transform domain histogram enhancement approach for images. Tang and Isa [34] presented the gray level Bi-HE (BBHE) approach for image contrast enhancement. Mukherjee and Mitra [35] proposed the DCCS-based scaling approach in the DCT domain using the Y-Cb-Cr color space, but this method can significantly increase brightness and is less effective in non-uniform illumination cases. Additionally, the Y-Cb-Cr color space method is susceptible to color perception issues, leading to color distortions. Sengar et al. [36] used DWT for DCCS-based color image enhancement, which outperforms the DCT approach. Buzuloiu et al. [37] proposed a neighborhood-adaptive method for implementing HE in image contrast enhancement. Sinha et al. [38] addressed the challenge of aging in human faces for facial recognition by using deep fusion combined with soft computing neural networks to improve prediction efficiency. Pizer [39] also utilized deep Convolutional Neural Network (CNN) networks for feature extraction. Savchenko [40] and Setiawan et al. [41] proposed HE-based methods for image contrast improvement. Kim et al. [42] introduced the enhancement of the saturation component in the HIS color space using entropy scaling. However, the non-linear conversion from RGB to HIS can complicate image processing tasks. Li et al. [43] proposed enhancing the contrast of underwater videos and images. The template matching approach was used for correlation analysis in images by Munsayac et al. [44], where the correlation was employed as a threshold for matching decisions. Alkraik [45] employed both grayscale and color images in various color spaces, such as RGB, YIQ, and YCbCr, subjecting them to a watermarking method that combines DWT, DCT, and SVD. They found that different color spaces yield different performance outcomes for the same image data. Furthermore, image preprocessing may be required to assess their performance, especially for tasks like security. However, the DCT method is sensitive to the blocking effect, and the SVD method is prone to noise. Pai et al. [46] addressed the issue of low-contrast and poor-quality images in the medical field. Their method, based on wavelet transformations, is particularly effective compared to Fourier and other domain-specific approaches. A novel technique for enhancing medical images uses wavelet transforms, such as the Haar wavelet, in conjunction with the Laplacian operator to focus the image. However, Roopali's method is sensitive to outliers and has a limited dynamic range. The wavelet transform is first used to decompose the medical image, followed by enhancement techniques

Therefore, it can be concluded that DCCS-based enhancement is commonly used, but it often requires additional methods to improve performance. Additionally, LBP features are well-suited for FR. It is essential to design an entropy-efficient FIE approach to enhance the overall efficiency of the FR system.

3.3 Review of image matching and FR

There are several methods for feature extraction in FR. Figure 3 illustrates the commonly used features in face detection algorithms.

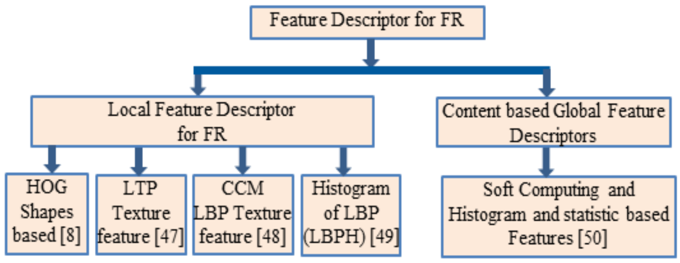


Figure 3. Classification of feature descriptors used for FR systems

It can be observed from Figure 3 that FR methods are categorized into global and local feature-based approaches. BL et al. [47] proposed adopting Local Ternary Patterns (LTP) features for FR system design. However, LTP features may not accurately represent intricate facial structures, although they capture local texture information effectively. Kose et al. [48] proposed using HOG for shape features and Local Binary Gradient Patterns (LBGP) for texture extraction in FR systems on the Facial Cosmetic Database (FCD). They combined these with an SVM classifier to detect makeup faces in computer vision and image processing tasks. However, the robustness of the gradient features can be reduced if the gradient distribution is significantly altered due to changes in illumination conditions. Panda et al. [49] recently used histogram-based LBP features (LBPH) as feature extractors, finding that this approach works well for FR systems under varying poses and illumination conditions. Global features, however, are susceptible to background noise and can be less effective when the object is partially occluded or experiences geometric deformation. It is challenging to develop accurate image matching with global features alone. In contrast, local features are more robust to image scaling, rotation, or translation, making them more suitable for matching in this work using local textures. Sharma et al. [50] previously developed a global framework that utilizes statistical soft computing approaches for content-based image retrieval (CBIR). For retrieving real color images, they employed HSV and RGB color spaces.

3.4 Recent face enhancement and recognition methods

Oulefki et al. [51] presented an efficient fuzzy logic-based FR approach, addressing the common challenge of FR in low-light conditions. This effort combines the CLAHE methodology for face enhancement with a novel fuzzy decision-making approach, improving the quality of face images captured in poor lighting. Oloyede et al. [52] highlighted the efficacy of meta-heuristic-based methods for image enhancement, proposing a novel assessment tool that integrates with optimization techniques to autonomously select the best augmented face image based on multiple quantifiable metrics. Yadav et al. [53] designed a simple yet effective quantitative software and texture-based retrieval engine, utilizing image histograms and statistical features such as probability distribution, average variance, and 2D normalized association of texture data for matching query and pattern images.

Wang et al. [54] addressed face identification challenges caused by high intra-class variation, low inter-class variation, and lighting conditions, proposing a lighting payment technique with an efficient intensity sensor and a flexible single-value decomposition method in the 2D discrete Fourier domain (ASVDF). Giap et al. [55] tackled variable lighting issues in practical FR algorithms by introducing the Adapted Multiple-Layer Retinex-Based Color Face Augmentation (AMRF) technique, which improves face images under challenging lighting. However, Retinex-based algorithms may cause color distortions due to inaccurate illumination assessment, especially in complex lighting situations. Eleyan [56] explored various statistical descriptors for use in FR applications.

Zhou et al. [57] examined six types of image degradation, including background texture, shouldering fade, poor lighting, watermarking, and blur, summarizing models to address each of these issues. Al-Dabagh et al. [58] proposed a local-directed pattern generator for facial identification, leveraging both the Frei-Chen and Lopez masks to create a powerful feature extractor. Mythili et al. [59] developed a CNN-based framework for feature extraction and learning, which estimates log-likelihood ratios to reduce FR failure. However, DL methods require large datasets and are computationally complex, making them unsuitable for real-time FR.

3.5 Review of light-based FR system

Galdi et al. [60] proposed the use of light fields to analyze face image illuminations. Kim et al. [61] recently investigated the liveness of face image recognition based on a light field camera, noting that variations in lighting conditions or illumination can significantly affect recognition efficiency, necessitating preprocessing. Similarly, Ullah et al. [62] and Qiao et al. [63] have also worked with images captured under low-light conditions. In summary, it is proposed to design an efficient FIE system to improve the accuracy of the FR system. Braik et al. [64] introduced a satellite images approach using augmented elk herd optimize to improve the CLAHE enhancement. Archana et al. [65] has proposed a good review of various deep learning models for digital image processing and enhancement. Sun et al. [66] proposed a Zero-DCE based approach for enhancing the low-light Images. A comparison of various impulse response filters is provided in the Table 3.

3.6 Review of recent low lighting enhancements

A significant area of research focuses on low-contrast image enhancement using wavelet transform-based algorithms, aiming to improve the quality of images affected by low contrast. Several approaches have been proposed to tackle this challenge, including the use of wavelet decomposition combined with the enhanced Retinex technique for fog removal, and the CLIP-Fourier Assisted Wavelet Diffraction technique for low-light image enhancement, which outperforms existing methods in both image recovery and visual perception [67]. Additionally, the wavelet-based conditioned diffusion model (WCDM), within the DiffLL approach, effectively enhances low-light images by achieving stable denoising and significant efficiency improvements over previous methods [68, 69]. These methods represent advancements in image processing and restoration techniques by employing wavelet transform to enhance contrast, restore details, and improve the authenticity of images [70].

Singh and Tiwari [67] introduced a new logarithmic Twicing function that uses the log function and numerical scaling to control contrast. Wang [68] suggested examining wavelet transform-based image de-hazing enhancement. The Enhanced Retinex algorithm, designed to remove haze from images, may introduce color distortions, especially in complex images with varying lighting conditions. Jiang et al. [69] studied the use of wavelet transform in the frequency domain for image enhancement, combining it with Fourier Transform (FT) for fine-grained image structure recovery. However, this technique suffers from the loss of spatial information and difficulties in depicting local details.

Table 3. Comparison of various featured used for recent FIE and FR algorithms

Authors	Methodology Opted	Images Used for	Features Description
Oulefki et al. [51]	Face image contrast enhancement CLAHE	Face images Yale database	FIE is merged with novel fuzzy decision-making approach for illumination improvement
Oloyede et al. [52]	Metahuristic FIE	Different Gray Face Database AR, ORL, Yale	Proposed new Evaluation function for assessment of FE based on statistical parameters
Yadav et al. [53]	Image retrieval method	Corel-1k image database	Statistical features and 2S correlation matching are used for image retrieval task
Wang et al. [54]	Color FIE	Color face images	Adaptive Fourier transform domain-based approach for color FIE
Zhou et al. [57]	Document image enhancement	Document images	Have reviewed effect of document degradation based on background texture, watermarking and lightning
Al-Dabagh et al. [58]	FR system using CCA	Face image data Yale, FCD	Fusion of the local LBP features using CCA is proposed and then SVM and KNN is used for classification of Face images
Mythili et al. [59]	DL-based FR using CNN	Video based face surveillance	Proposed video surveillance-based feature extraction and DL models-based FR system for theft identification
Our proposed work	Entropy efficient FIE using DCCF and LBP texture and HOG shape features for FR	FCD makeup face images database and Yale, AR and ORL	DCCS based on entropy efficient image fusion for FIE and application over FR using Texture based LBP and HOG Feature for shape. the simple and efficient template matching algorithm for FR

Mallaparapu and Ramarao [70] used wavelet transforms to enhance images, combining it with the synthetic and soft thresholding algorithm SCAD for noise reduction. Although effective in noise reduction, the method has limited enhancement potential. Kannoth et al. [71] developed a Curvelet Transform (CT) combined with iterative back-projection for image enhancement. However, this method is not suitable for FIE due to its slow convergence and sensitivity to distortions like streaking and ringing. Acharya et al. [72] proposed a meta-heuristic image enhancement technique and compared its performance with other optimization approaches. They achieved images with higher contrast levels.

Cao and Yu [73] have investigated low light based image enhancement approach using the curve estimation approach. Shen et al. [74] presented a method that, while effective, is computationally complicated and requires large datasets, making it unsuitable for FR systems with small datasets. Zhao and Li [75] proposed a Retinex and transformation-based method for image enhancement, utilizing a dual-branch network for local detail synthesis.

DCE-Net, based on DL, was introduced by Rajesh and Karunakar [76] for image enhancement. While effective, this method introduces color distortions in low-light images and has high operational costs. A recent transformer-based image enhancement strategy by Al-Dabbas et al. [77] showed potential for FR systems but primarily focuses on feature-based approaches and is likely to have low performance on makeup images.

Based on an extensive review of these methods, we propose an entropy-efficient method capable of preserving both color information and brightness, aiming to improve the performance of FR systems, particularly for makeup images.

4. PROPOSED SYSTEM DIAGRAM

In this work, a hybrid combination of the FIE approach is designed to improve the efficiency of FR systems. The proposed method begins by taking a query face image and template images from a database, followed by feature extraction. Matching techniques are then employed to detect or match the desired images with enhanced efficiency. Wavelet-based fusion is used for feature enhancement. Various image features are utilized to represent or match the desired query images, with LBP features being proposed for use in this research. The basic processing flow for the cosmetics face retrieval system is shown step-by-step in Figure 4.

FR involves three key steps. Figure 4 clearly illustrates that the quality of feature extraction is the most crucial factor in improving a face detection system's performance, making it essential to maintain high-quality extraction. The current study focuses on identifying facial cosmetics that could enhance the precision of FR systems.

Users can employ FR to retrieve their desired face image from a database, based on both local and visual features. FR algorithms are widely used in real-time video surveillance, human identification [2], and data mining technologies. This study emphasizes the extraction of features that consider the local context to improve the accuracy and effectiveness of the extraction process.

This research develops and compares an adaptive DC coefficient augmentation approach implemented in the LAB color space to the standard Y-Cb-Cr color space for true color images.

Figure 5 contrasts the RGB and LAB components for makeup image 10 as input, highlighting how each color component can impact facial makeup differently. Due to significant differences in each RGB color component, applying the DC coefficient augmentation in this space is challenging. Therefore, the LAB color space is chosen over RGB because it provides optimal brightness distribution. The CIE Lab color space offers more consistent color representation than other available models, allowing for better color balance and precise contrast adjustments. As a result, using the CIE Lab color space enhances the augmented image's informational content and entropy. For efficient feature extraction, LBP-based features are proposed to extract and match query and template images.

The contrast level is improved using entropy maximization, and multi-focus self-image fusion is applied to enhance image quality.

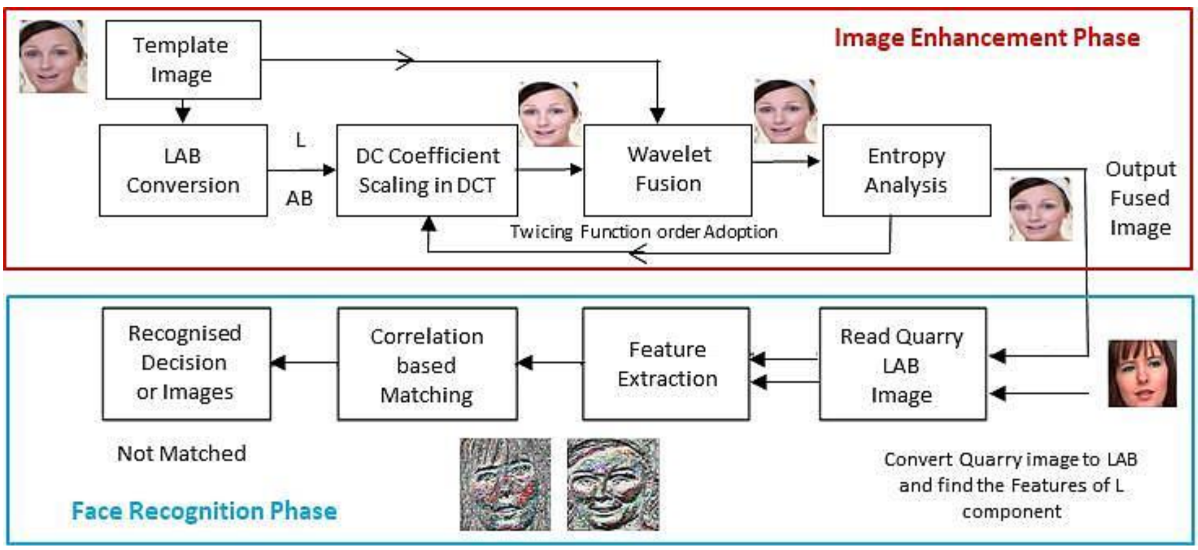


Figure 4. Sequential diagram of proposed Image enhancement for facial makeup detection

Figure 5. Comparison of the RGB vs LAB components for makeup image case

4.1 Contrast enhancement

Spatial domain histogram-based algorithms modify pixel intensity to enhance images. The most widely used spatial domain methods are HE and CLAHE [37, 38]. CLAHE is particularly effective in scenarios requiring brightness enhancement, such as in geographic channels or underwater conditions. However, HE can significantly alter image brightness, leading to issues in applications where preserving brightness is essential. Additionally, CLAHE may be sensitive to true color variations, especially in FIE. Researchers in the DCT field [35, 36] and those using DWT [36] have developed various contrast enhancement algorithms in the compressed domain. These methods aim to demonstrate improvements in image appearance. The DCT transform domain is particularly effective in color spectrum separation, allowing features to be enhanced by treating different frequency components separately. Several algorithms have been proposed using block DCT domain implementation over images converted from the RGB to the Y-Cb-Cr color space. This conversion enables a more effective analysis of color based on luminance and chrominance components, providing a better starting point for image enhancement. This manuscript discusses and evaluates a method for improving color images in the DCT domain by scaling DC coefficients. The limitations of existing approaches are illustrated in Figure 6, highlighted by yellow and red boxes. Current DCCS approaches use Y-Cb-Cr components in 8×8 blocks to enhance the luminance component, as seen in studies [35, 36]. However, this approach is sensitive to changes in the MB value of true color face images.

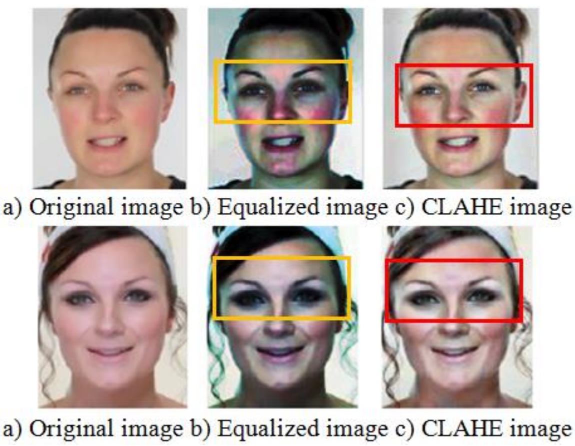


Figure 6. Limitations of existing approaches in context to FIE methods

The efficiency of FR is highly dependent on the effectiveness of image enhancement methodologies, as these directly impact the recognition performance. Therefore, it is crucial to preserve the brightness and enhance the entropy of face images. The first step is to evaluate the outcomes of various image enhancement methods within the context of FR. Following this, the second phase involves designing an entropy-efficient FIE approach to further improve recognition accuracy.

4.2 Proposed order adaptive entropy efficient FIE

The primary goal of this manuscript is to design entropy-efficient, high-quality face images that are visually enhanced through contrast adjustment. The paper proposes using the CIE-Lab color space for transformation and localized DC coefficient augmentation in the compressed DCT domain for the FIE task. In this approach, contrast is increased in the L component while preserving the color information. An innovative adaptive Twicing function is applied to provide an entropy-efficient enhancement solution. The process of DCCF image enhancement in the DCT domain is explained in this section.

For improved FR efficiency, a face image from the template database is suggested for enhancement. The color face images are first transformed from RGB to LAB before applying block-based DCT to determine the DC coefficients. Since the DC value represents the MB of each block, DCCS is performed on each local DCT block for contrast enhancement by adjusting the background illumination of the DC coefficient. Based on the entropy learning approach, an order-adjusting brightness mapping function is proposed as a novel improvement. In the second phase, if required, image fusion of the enhanced face images is proposed to preserve content. The steps of the basic DCCS enhancement are outlined in Algorithm 1 as follows:

4.3 DCCS

The DC coefficient of the augmented "L" component in the LAB image is suggested to be modified. The pre-enhanced DC coefficient (Y(0,0)) contains the most significant information, which is why this adjustment is made. This method operates more efficiently than the existing DC coefficient techniques because it does not require increasing the order of the DCT coefficients. Additionally, it is faster than methods that rely on the spatial domain, as outlined in Algorithm 1. The DCT-based DCCS method offers several benefits in the context of FIE, such as:

- The average intensity of a block of images is represented by the DC coefficient. DCCS can effectively change the image's overall brightness or contrast by scaling it.
- The overall brightness of the image can be improved by increasing the DC coefficient, while its overall brightness can be decreased.
- The high-frequency (HF) components, which typically contain the details and edges, are unaltered since only the DC coefficient is changed.

Mathematically, DC coefficients are represented by a scaling factor $K = \left(f\left(\frac{Y(0,0)}{NI_{max}}\right)\right) / \left(\frac{Y(0,0)}{NI_{max}}\right)$, as given in Eq. (4), and the mapping of brightness over DC coefficients is calculated using the Twicing function as DCC=τ(x)*L_max. Since it is observed that after taking the inverse DCT, the enhanced image with DCCS may have a larger brightness variation for face images, thus this paper additionally proposes to adopt the order of Twicing function based on entropy analysis.

The fundamental concept behind the DCT domain algorithm for contrast enhancement via DCCS was initially proposed by Mukherjee and Mitra [35], where the idea was to scale the DCT coefficients to improve contrast. In this paper, the focus is on modifying the DC coefficient of the image's L component in LAB space. To achieve optimal contrast enhancement, an adaptive scaled log Twicing function [67], as defined in Eq. (2), is introduced. Once the contrast is improved, the enhanced image and the original image are considered as a pair of multi-focus images and are subsequently fused together.

Wavelet-based image fusion is applied to the enhanced image pair, which helps maintain brightness while improving the entropy of the system. The fusion algorithm is described in Algorithm 2. Pixel-level average maxima are computed using the 'bior2.2' wavelet filter for fusing the images. The process of wavelet fusion is depicted in Figure 7.

The goal of the proposed method is to fuse the images in a way that preserves the MB of the enhanced image, ensuring that the enhanced image retains its visual integrity while maximizing its informational content.

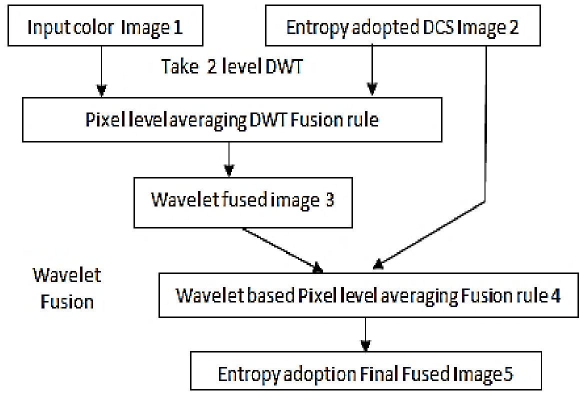


Figure 7. Process of wavelet fusion for entropy adoptive enhancement

Algorithm 1: Entropy Efficient Adaptive DCCS Enhancement

1. Read the template database image ← $InImg_{RGB}$
2. Convert RGB to LAB ← separate lab_{he} the L component ← applyCform
3. Apply DCT and loop over image size ←Select the block size of DCT ← B as $N \times N$

for i=1: s(3)
  for j=1: s(4)

4. Obtain the maximum luminance value as:

$$\max(lab_{he}) = L_{max} \quad (1)$$

5. Apply DC coefficient mapping using adaptive log Twicing function

$$\tau_{log}(x) = x * (2 - 0.3 * log(x)) \quad (2)$$

6. Calculate mapping of brightness over DC coefficients (DCC) as:

$$DCC = \tau log(x) * L_{max} \quad (3)$$

7. Apply the DDCCS using the luminance values as:

$$\mathrm{K} = (\mathrm{f}\left(\frac{\mathrm{Y}(0,0)}{\mathrm{N}I_{max}}\right))/(\frac{\mathrm{Y}(0,0)}{\mathrm{N}I_{max}}) \quad (4)$$

end
end

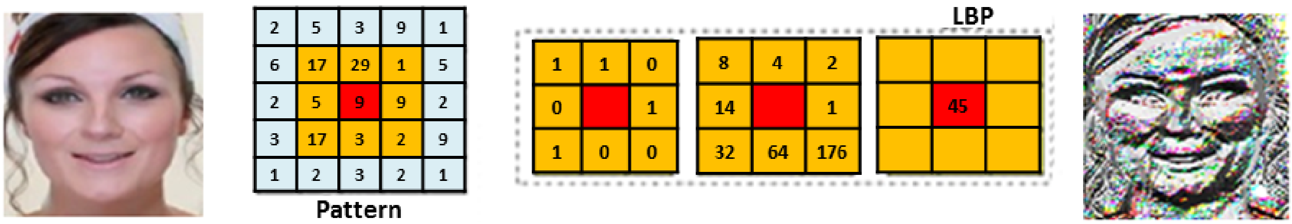
8. Merge the all DCT blocks at the scale of B

$$DCCS_{Img} = \mathrm{dctImg.}* 8 \quad (5)$$

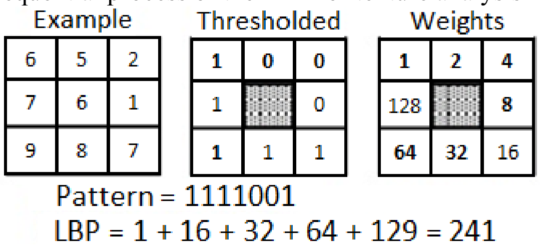
9. Apply inverse DCT transform and convert LAB to RGB back
10. Decision making based on entropy learning to apply wavelet based Fusion ← inImg fuse $DCCS_{Img}$
11. Determine the entropy of images at each stage

    if $E_{DCCS_{Img}} > E_{InImg}$
      CH=1; → end of algorithm else
        CH=2; → adopt the order of the Twicing function
    end

12. Repeat 10 to 11
13. **end Algorithm**



a) Face image (b) Sequential process of the LBP for texture analysis (c) Extracted LBP feature



(d) An example

Figure 8. Computing the LBP features extraction process a sequential example illustration

Algorithm 2: Entropy Efficient Adaptive DCCS Enhancement

1. Read the InImg and enhanced $DCCS_{Img}$ image
2. Take the N level DWT decomposition of both images

$$In_{decompse}{}^{N} = [I_{LLN}: I_{LHN}; I_{HLN}: I_{HHN}: I_{LLN}: I_{LH(N-1)}; \cdots I_{HL}: I_{HH}] \quad (6)$$

$$DCCS_{decompse}{}^{N} = \begin{bmatrix} EI_{LLN}: EI_{LHN}; EI_{HLN}: EI_{HHN}: EI_{LLN}: EI_{LH(N-1)}; \\ \cdots\cdots EI_{HL}: EI_{HH} \end{bmatrix} \quad (7)$$

3. Select the LL coefficient DCT← I_{LLN}, EI_{LLN}
4. For the image size at N level

for i=1: s(3)

for j=1: s(4)

apply the mean-max Image fusion rule as

$$Fjk = max\ (I_{LLN\ j,k}, EI_{LLN\ j,k}) \quad (8)$$

end

end

5. Rake IDWT of fused LL Block keeping the all-other coefficients of EI
6. Check for the entropy analysis

if $EI_{F-DCCS_{Img}} > E_{InImg}$

CH=1; → end of algorithm

else

CH=2; → adopt the order of the Twicing function and repeat Algorithm 1 and 2

end

7. Entropy and brightness criterion meet
8. **end Algorithm**

The pixel level averaging rule for the DWT-based fusion is given as in Eq. (8) as:

for i=1: s(3)

for j=1: s(4)

apply the mean-max Image fusion rule as

$$Fjk = max\ (I_{LLN\ j,k}, EI_{LLN\ j,k})$$

end

end

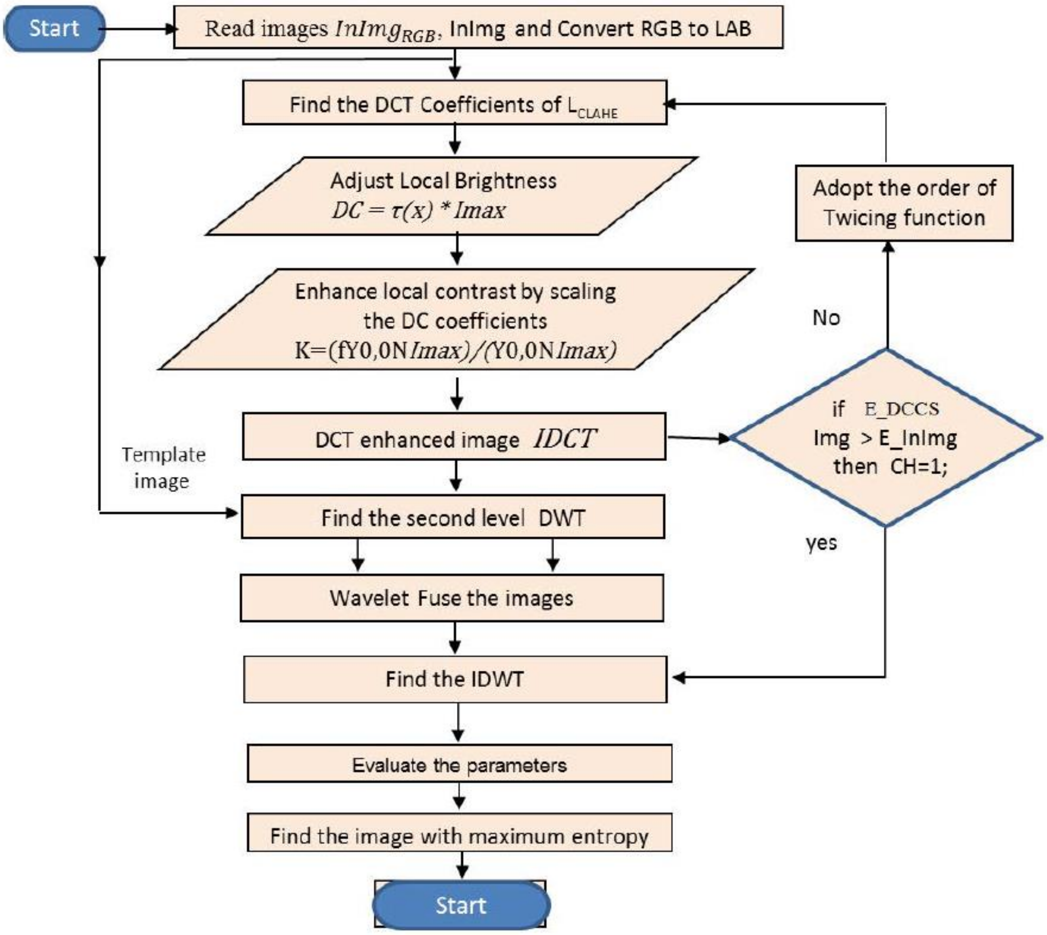


Figure 9. Flow Chart of complete two pass entropy adaptive FIE

4.4 FR and feature extraction approach

Several feature descriptors have been employed in the past to identify textures and shapes. This paper focuses on two fundamental feature-based descriptors for makeup detection. Specifically, it proposes the use of Local Gabor Binary Patterns (LBP) as texture feature descriptors for facial images. In this approach, the LBP operation is applied within the Gabor feature matrices to encode the magnitude of luminance values. LBP feature descriptors are advantageous in texture analysis due to their simplicity, grayscale nature, and rotation invariance. The relationships between the central pixel P(xc,yc) and its neighboring pixels are computed to derive the LBP. Thresholding is used for encoding, which allows for effective binary pattern/texture detection. To generate the binary pattern in the neighboring pixels, the center pixel's gray value is used as the threshold. In this method, the pixel values of the neighborhood are assigned a value of 1 if they are greater than the center pixel and a value of 0 if they are smaller. The step-by-step process of the LBP technique is illustrated in Figure 8. This method effectively captures the texture patterns within a localized region, making it ideal for facial image analysis.

$$Contrast: C = (6+7+8+9+7)/5 - (5+2+1)/3 = 4.7 \tag{9}$$

Flow Chart: the flow chart of the complete proposed two pass method for FIE is illustrated in the Figure 9. It can be clearly seen in the flow chart that the method is a two-pass approach. It is a combination of DCCS based on the order-adaptive concept and wavelet fusion for brightness preservation.

5. RESULTS AND DISCUSSION

This section presents a comparison of experimental results for the various mentioned color image enhancement methods. Results are presented in two passes; first, the FIE proposed results are presented in Figure 10 for the 5 different approaches of FIE. The results are evaluated for the FCD and the Yale image databases.

Figure 10. Qualitative evaluation for 2, 5, 7, 12 and 23 of FCD database images for HE, CLAHE, DCCS [35], DCCS LAB [14], proposed DCCS with Order adaptive Twicing Function, Proposed Fused, Entropy efficient proposed

Figure 11. Qualitative evaluations for gray FCD face database images for HE, CLAHE, DCCS [35], DCCS LAB [14], proposed DCCS with Order adaptive Twicing Function, Proposed Fused, Entropy efficient proposed

Figure 12. Qualitative evaluations for Yale face database images for HE, CLAHE, DCCS [35], DCCS LAB [14], proposed DCCS with order adaptive Twicing function, proposed fused, entropy efficient proposed

Figure 13. Qualitative evaluations for AR face database images for HE, CLAHE, DCCS [35], DCCS LAB [14], proposed DCCS with Order adaptive Twicing Function, Proposed Fused, Entropy efficient proposed

The evaluation of the FIE system is conducted using a database of images with makeup and varying poses. For comparison purposes, spatial domain methods based on HE and CLAHE are considered. Additionally, the DCCS-based enhancement methods in both Y-Cb-Cr space, as proposed by Mukherjee and Mitra [35], and in LAB space, as suggested by Jarholiya et al. [14], along with the proposed entropy-adaptive fusion, are also included for result comparison.

As shown in Figure 10, spatial domain methods such as HE and CLAHE are sensitive to color variations. The existing DCCS approach [35] can significantly increase the MB, which may not be ideal for all cases. To address this, we propose using the LAB color space combined with the modified order adaptive-Twicing function, with an adaptive learning parameter, to achieve better control over both color and brightness. Furthermore, the proposed wavelet-based fusion method enhances the content and entropy of the FIE system, leading to improved overall performance.

The effectiveness of the proposed method is also tested on the grey-level Yale and FCD databases, as shown in Figure 11. For the representation in Figure 11, images of three objects (14 and 22 for FCD) are randomly selected, each displaying different expressions. The results from the proposed method demonstrate brightness-preserving, entropy-efficient face images. Qualitative evaluations for the Yale database are shown in Figure 12, comparing methods such as HE, CLAHE, DCCS [35], DCCS LAB [14], the proposed DCCS-LAB, the proposed fused method, and the entropy-efficient results across different facial expressions.

Further comparative qualitative results, showcasing various expressions and emotions, are presented in Figure 13 using the AR image database. The superior quality of the proposed fusion-based entropy-efficient approach is clearly evident in these results.

5.1 Qualitative evaluation

In order to justify the results, the qualitative evaluation is performed in this section. The various parameters are considered as MB, SD, PSNR, and entropy.

The MB is defined as follows:

$$MB = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Im(i,j)_{1}^{3} \tag{10}$$

The SD is calculated as follows:

$$SD = \left[\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Im(i,j)^2 - \frac{1}{n}\left[\sum_{j=0}^{n-1}\sum_{j=0}^{n-1} Im(i,j)\right]^2\right] \tag{11}$$

The PSNR is mathematically calculated as follows:

$$\mathrm{P}SNR = 10 * \log\left(\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[\max\left(Im(i,j)\right)/\left(Im(i,j) - K(i,j)\right)\right]^2\right) \tag{12}$$

The primary objective of this paper is to develop an entropy-efficient solution that performs consistently well across various face image databases. In this context, the entropy E is defined as follows:

$$E = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} p(i,j) * \log(p(i,j)) \tag{13}$$

Table 4. Comparison of MB for enhancement methods

Images	Original	HE	CLAHE Method	DCCS Y-Cb-Cr Mukherjee and Mitra [35]	DCCS LAB with Log Twicing Function [67]	DCCS LAB with Proposed Fusion	Order Adaptive Proposed Fused Result
ORL1	147.7326	127.4785	145.7435	195.6119	169.9662	158.8512	158.8479
ORL2	121.4769	127.5168	125.8024	194.1093	163.2457	152.9625	152.9644
FCD 2	172.4112	127.4882	165.1093	205.1596	177.6058	164.3715	164.3707
FCD 5	154.1188	127.5604	148.2292	183.6449	143.7093	133.0063	132.9902
FCD 12	150.3280	127.7287	145.2502	146.9656	119.3639	112.5925	112.5720
FCD 14	110.0770	127.4205	126.6631	158.8811	129.4097	119.7417	119.7568
FCD 23	117.007	127.5600	129.351	135.0777	108.7664	99.4932	99.4934
AR1	119.1197	127.5588	129.5832	181.0460	138.6438	128.8791	128.8663
AR2	114.2157	127.4093	124.5739	178.9244	133.8363	124.0215	124.0087

Table 5. Comparison of SD for enhancement methods

Images	Original	HE	CLAHE Method	DCCS Y-Cb-Cr Mukherjee and Mitra [35]	DCCS LAB with Log Twicing Function [67]	DCCS LAB with Proposed Fusion	Order Adaptive Proposed Fused Result
ORL1	60.4545	74.8818	63.7124	54.8054	70.0970	65.4069	65.4069
ORL2	58.0739	74.7793	60.6462	46.9713	64.2893	61.3413	61.34132
FCD 2	52.3879	74.7645	57.3905	50.9328	62.9109	59.1709	59.1709
FCD 5	46.3895	74.8518	54.2806	47.5291	57.3292	53.7020	53.7020
FCD 12	79.5753	75.0518	73.3016	64.9620	77.9825	74.2527	74.2527
FCD 14	51.2818	74.8581	58.4762	53.47464	60.8352	56.4434	56.4434
FCD 23	33.9106	74.6887	44.2600	31.9185	36.5506	35.1366	35.1366
AR1	43.2320	74.8050	53.3485	41.1183	51.9172	47.7940	47.7940
AR2	32.9153	74.7691	41.5030	33.28340	40.8214	37.0528	37.0528

The evaluation of MB for various image databases is presented in Table 4. It is evident that the HE method significantly reduces the MB. The CLAHE method, while effective, is sensitive to color variations in the images. Although entropy-efficient, it doesn't perform adequately for color images. The existing DCCS method in the YCbCr space [35] leads to a notable increase in MB. In contrast, the proposed method enhances images in the LAB color space using the modified order adaptive Twicing function, which aids in brightness preservation and improves entropy efficiency.

The quantitative evaluation of MB for different test images is shown in Table 4. After performing the T-test, it is observed that the average MB for the DCCS-YCbCr method [35] increases from 133.89 to 169.95, indicating sensitivity to MB changes. The entropy-adaptive proposed method, however, maintains the MB at 126.0083, which is close to the original brightness.

Quality cannot be fully assessed using a single parameter. Therefore, Table 5 presents the SD for different enhancement methods. The SD should be as close as possible to that of the original image. It can be seen that the proposed method yields a lower SD than the DCCS LAB with the Log Twicing function. The average SD for the original images is 50.913, while CLAHE and DCCS-YCbCr [35] yield SDs of 56.324 and 47.221, respectively. The proposed method preserves the SD, reducing it to 54.477 due to the fusion process. The SNR presented in Table 6 shows that the proposed order adoption method does not result in significant relative changes, demonstrating the efficacy of the Twicing function order. This is further supported by the entropy analysis. As shown in Table 7, the entropy of the proposed order-adaptive method outperforms the existing approach.

From Table 5 and Table 6, it is clear that the HE method increases brightness, resulting in higher MSE and lower SNR. While useful for low-illumination images, the DCT method performs significantly better for true-color images, such as Image 1 and Bali Image. For images with non-uniform illumination, however, CLAHE delivers better SNR and MSE performance than the DCT method.

5.2 T-test performance of state of art methods

To further justify the results of the parametric comparison, specifically for SNR and entropy, a T-test was conducted, and the respective SNR values were compared between the CLAHE method (as proposed by Jarholiya et al. [14]) and the standard DCCS-YCbCr method by Mukherjee and Mitra [35]. The results are illustrated in Figure 14.

Figure 14a shows that the proposed method provides a 5.8 dB improvement in SNR over the method by Mukherjee and Mitra [35] and a 13.2 dB improvement over the CLAHE enhancement.

Figure 14b indicates that the proposed method improves entropy by 0.133 over the DCCS LAB with Log Twicing Function approach of Singh and Tiwari [67]. It also shows an improvement of 0.589 in entropy over the method by Mukherjee and Mitra [35], achieving the best average entropy value of 7.521.

5.3 Result of FR

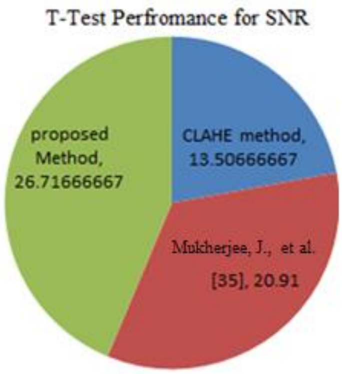
This section presents the results of the extracted features from various algorithms for comparison. In this study, template images from two distinct face classes in the FCD database are used for evaluation. The template images in each class differ in color and features, and they are actual color images.

Table 6. Comparison of SNR for enhancement methods

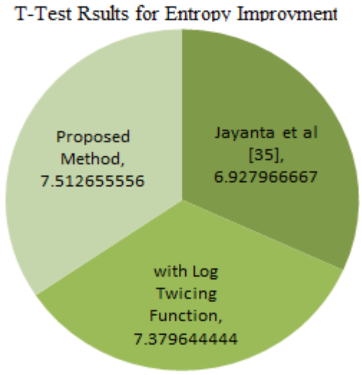
Images	HE	CLAHE Method	DCCS Y-Cb-Cr Mukherjee and Mitra [35]	DCCS LAB with Adaptive Twicing Function	DCCS LAB with Proposed Fusion	Order Adaptive Proposed Fused Result
ORL1	25.600	29.710	14.1800	19.9600	25.7900	25.7900
ORL2	26.930	29.060	13.4300	20.710	26.5000	26.5000
FCD 2	25.160	28.300	13.24	18.9300	24.7900	24.7900
FCD 5	25.940	28.100	12.2300	20.4000	26.2700	26.2700
FCD 12	25.280	28.090	15.3100	22.4000	28.0400	28.0400
FCD 14	30.870	34.090	14.1100	21.1100	26.8200	26.8200
FCD 23	28.670	33.100	15.0500	22.4200	28.3200	28.3200
AR1	28.350	30.970	12.1600	20.9500	26.7100	26.7100
AR2	28.350	30.970	11.8500	21.3100	27.2100	27.2100

Table 7. Comparison of entropy for enhancement methods

Images	Original	HE	CLAHE Method	DCCS Y-Cb-Cr Mukherjee and Mitra [35]	DCCS LAB with Log Twicing Function [67]	DCCS LAB with Proposed Fusion	Order Adaptive Proposed Fused Result
ORL1	7.5306	5.9850	7.6719	6.7451	7.2919	6.6697	7.5422
ORL2	7.6827	5.9839	7.7913	6.9809	7.4747	6.8339	7.7107
FCD 2	7.2005	5.9595	7.5818	6.7426	7.5708	6.8915	7.6190
FCD 5	7.4765	5.9800	7.7007	7.1273	7.7190	6.9332	7.7133
FCD 12	7.5926	5.8865	7.4863	7.1273	7.5829	7.0627	7.8291
FCD 14	7.4521	5.9402	7.6702	7.0346	7.2495	6.5570	7.5089
FCD 23	7.4521	5.9402	7.6702	6.9040	7.1421	6.4718	7.0861
AR1	7.33813	5.9684	7.6531	7.0002	7.3477	6.5447	7.4789
AR2	7.33813	5.9684	7.6531	6.6897	7.0382	6.2046	7.1257



(a) T-test performed for the SNR



(b) T-Test performed for the entropy improvement

Figure 14. T- Test performance evaluations for parameters

5.3.1 Texture features results

Figure 15 shows the results of texture feature extraction. It is clear that the LBP features vary between each face image and provide valuable texture information for each image. The presence of cosmetics significantly influences the texture characteristics of the image.

The LBP patterns are effective in indicating the presence of makeup and also capture important face texture details, as clearly observed in Figure 15. These features are then utilized for FR, as proposed, based on correlation analysis.

The correlation measure for various images used in FR is calculated, as shown in Figure 16, where the correlation between query and template images is compared for recognition thresholds. The results of FR are presented based on matched correlation measures in Figure 17. Column 1 displays Query image 10, while column 2 shows Query image 7. Figure 16 is used to determine the parametric evaluation of Tp and Fp, which are calculated based on the two cases shown in Figure 17, as presented in Table 8.

a) True color images input for FCD database as image 2, 5, 8, 12, and 23

b) Respective extracted LBP features of images with makeup FCD database

Figure 15. The results of LBP texture features extraction for face images

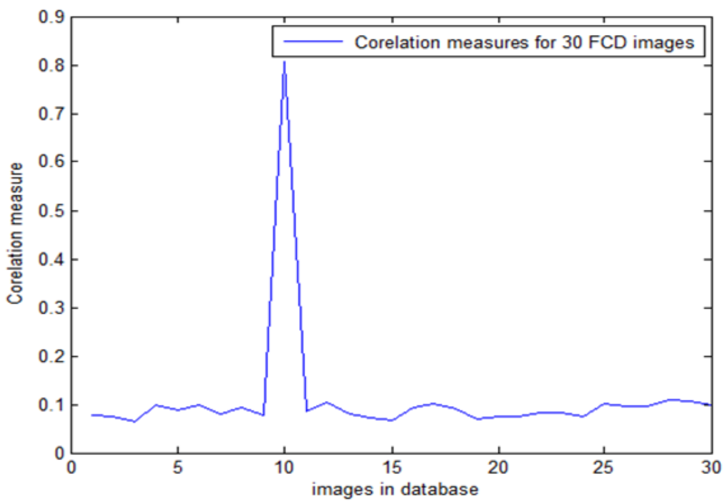
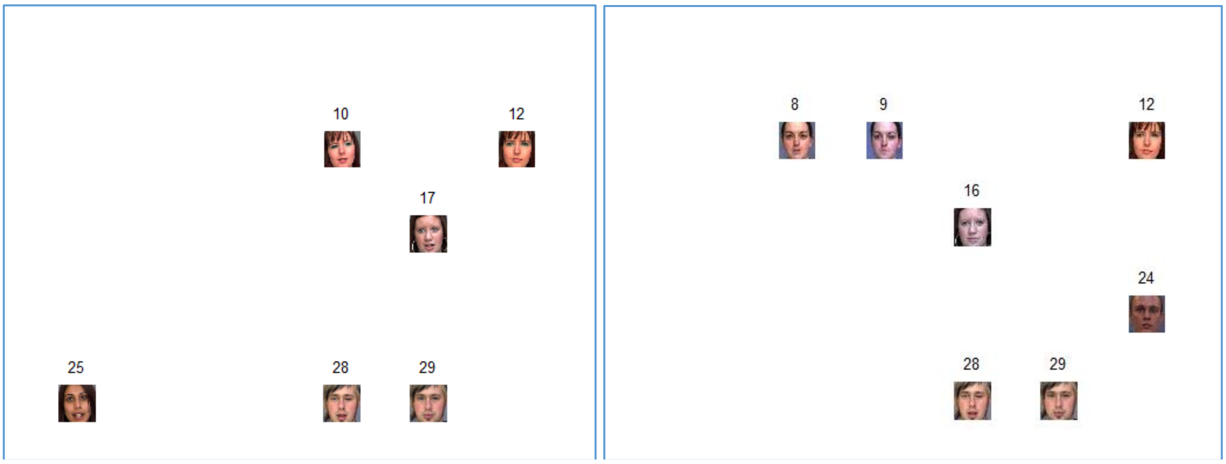
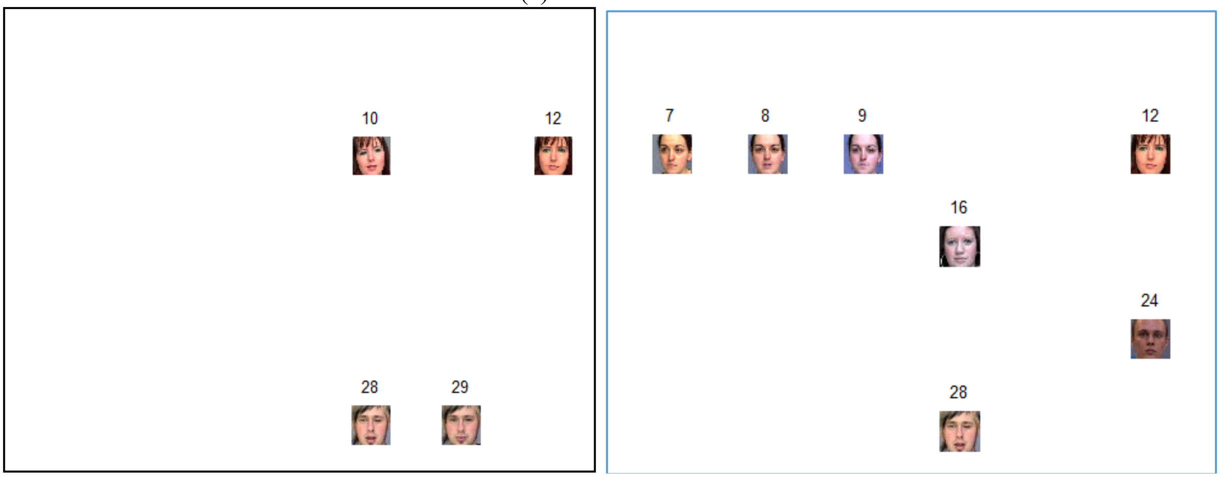


Figure 16. Corelation measures for the FCD image database for 30 images



(a) FR with LBP



(b) FR for enhanced LBP

Figure 17. Results of FR for, column 1 query image 10, column 2 query images 7

Table 8. Measure of the true positives and negatives for FR system

Variables	With LBP		With Enhanced Image LBP	
	Image 10	**Image 7**	**Image 10**	**Image 7**
Tp	25	24	27	26
Tn	5	6	3	4
Fp	4	4	2	4
Fn	1	2	1	0

Table 9. Measures of the % parametric evaluation of the FR technique

Variables	With LBP		With Enhanced LNP	
	Image 10	**Image 7**	**Image 10**	**Image 7**
Precision	86.20	85.71	93.10	86.67
Recall	96.15	92.37	96.43	100
FPR	44.44	40	40	25

The precision and recall are calculated for the two cases of query images as image 1 and image 7.

$$Precision = TP * 100/(TP + FP) \qquad (14)$$

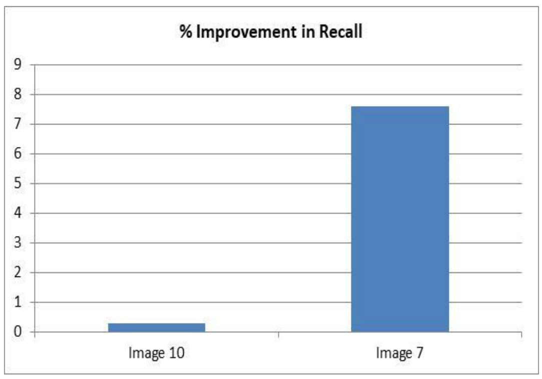
$$Recall = TP * 100/(TP + FN) \qquad (15)$$

$$TPR = TP * 100 /(TP + FN) \qquad (16)$$

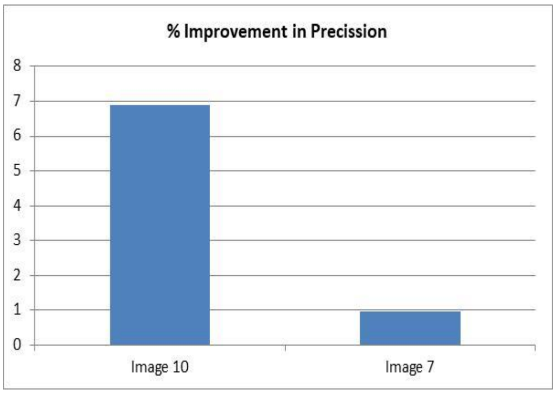
$$FPR = FP * 100 /(FP + TN) \qquad (17)$$

It can be concluded from Tables 8 and 9 that the use of image enhancement techniques improves the accuracy of FR in terms of both precision and recall. The results for precision, recall, and false positive rates (FPR) are shown in Table 8. It is evident that both precision and recall are improved for the randomly selected query images.

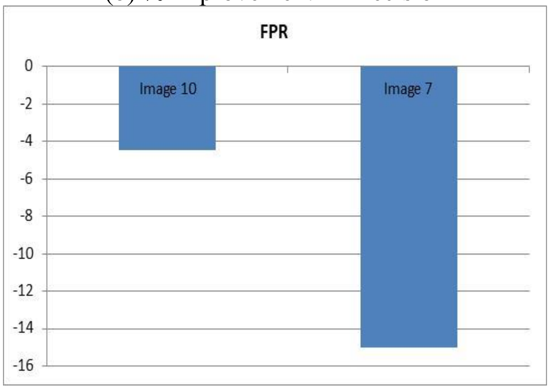
The comparative parametric performance improvements achieved through image enhancement techniques for FR are presented as bar graphs in Figure 18. The percentage improvements in precision with and without enhancement methods are clearly demonstrated. With the proposed enhancement method, Query image 10 shows a 0.4% improvement in precision and a 6.9% improvement in recall. Query image 7 exhibits a 7.56% improvement in precision and nearly 1% improvement in recall.



(a) % improvement in Recall



(b) % improvement in Precision



(c) FPR Reduction %

Figure 18. Comparative parametric performance improvements using the image enhancing techniques

6. CONCLUSIONS

The FIE methods presented in this paper propose a hybrid fusion approach to improve both contrast and visual appearance of facial images. In the first stage, a transform domain localized DC coefficient augmentation is applied using a compressed DCT domain approach within the CIE-Lab color space. This enhancement method increases contrast exclusively in the L component, while preserving the color information. Facial makeup detraction is achieved through texture and shape feature extraction methods, which are applied to the enhanced facial image. It is observed that the presence of makeup on the face leads to a degradation in recognition efficiency. To address this, a combination of LBP and HOG feature vectors is proposed for improved FR. The paper also compares the performance of spatial domain methods with transform DCT domain methods for FIE, using MB, entropy, and SNR as qualitative evaluation parameters.

- It is concluded that the HE method increases the brightness, thus giving a higher MSE and low SNR, although the method is useful for low illumination images.
- The DCT method performs significantly better for true-color face images. While for images with non-uniform illumination, CLAHE gives better SNR and MSE performance than the DCT method. But these methods are sensitive to large MB variations and thus are not suitable for FIE and FR contexts under the makeup database.
- Thus, in this paper, the adaptive SDC method based on order adoption of the Twicing function is proposed, which significantly preserves the MB and also improves the entropy of the exiting approaches.
- The proposed method equally works well for different kinds of gray and color face images with different poses and markup. It is concluded that the proposed approach gives less SD than DCCS LAB With Log Twicing function, thus being acceptable for contrast enhancement.
- Finally, the results with and without the FIE method are compared, and it is concluded that using FIE may significantly improve the accuracy of the FR system.
- Based on the T test, it is concluded that the suggested method improves SNR by 5.8 dB over the Mukherjee and Mitra [35] method and 13.2 dB over the CLAHE enhancement.
- The entropy improvement using the proposed method based on the T-test is 0.589 over the Mukherjee and Mitra [35] technique. It justifies the entropy efficiency aim of the proposed method for FIE.
- There is a significant potential impact of using entropy-efficient DC and coefficient scaling for FIE. When used correctly, it may significantly boost FR effectiveness. It is concluded that by effectively scaling the DC coefficient, we can magnify small facial traits that may be important for discriminating, hence enhancing recognition accuracy. Additionally, since only the DC coefficient is changed, the high-frequency features, which are critical for FR, remain intact. Also, the impact of using fusion in combination helped preserve the neon brightness, thus practically offering the higher FIE entropy efficiency too using the proposed method.
- The two distinct FCD databases query images are used for FR evaluation. It can be concluded that the precision and the recall are improved for both the query mage cases randomly selected. With the proposed enhancement method, the image 10 as query image offers 0.4 % improvement in precision and 6.9% in recall. The image 7 as query image may offer the improvement of 7.56% in precision and nearly 1% in recall.

7. LIMITATIONS OF THE STUDY AND SCOPES

Based on the proposed study, it can be concluded that the primary goal of this paper is to demonstrate the efficiency of the FIE method. However, more sophisticated machine learning-based FR methods could be explored in the future. The current method relies on a simple and fast correlation matching approach for FR, which, while effective, has relatively low precision and is inconsistent across images. While the method performs well for color makeup images, there is room for improvement with larger datasets and the integration of advanced techniques such as DL.

In the future, hybrid color spaces along with optimization techniques could be used to enhance FIE, and more complex FR systems could be considered for performance evaluation. Although the paper has successfully demonstrated the accuracy of FIE for FR, there is potential for further advancements. A hybrid feature set that includes shape, texture, and color could significantly improve FR efficiency. Additionally, incorporating optimization for FIE could help mitigate the challenge of over-smoothing, achieving the desired level of contrast for each specific image.

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NOMENCLATURE

$\tau_{log}(x)$	Twicing Function
L	Luminance Component
K	DC coefficient scaling factor
CH	Choice of image
$E_{DCCS_{Img}}$	Entropy of DCCS image
E_{InImg}	Entropy of input image
Y(0,0)	DC coefficient
Fjk	Fused image pixels
C	Contrast
m	No. of Rows
n	No. of columns
i,j	Pixel coordinates
TP	True Positives
TN	True Negatives
FN	False Negative
FP	False Positive

Greek symbols

p	Probability