A Hybrid Intelligent Facial Recognition Model Based on Hierarchical Feature Extraction and Il-lamination Normalization

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Abstract

Face recognition in unconstrained environments is difficult due to varying poses and lighting conditions. This can severely impair the performance of intelligent recognition models. Traditional methods often do not adapt well to these variations, which results in poor performance and limited applicability. This paper proposes a hybrid intelligent face recognition model based on hierarchical feature extraction and illumination normalization (H-FR). The proposed method employs a hierarchical feature extraction model to capture macro and micro facial details, ensuring reliable recognition across diverse poses and lighting conditions. Employing Adaptive Histogram Equalization on the A and B channels of the LAB colour space effectively normalizes illumination variations, enhancing the visibility and consistency of facial features. The proposed model has been tested and validated on the "Pins Face Recognition" dataset available on Kaggle, which encompasses various celebrity faces captured in varying poses and lighting conditions. The proposed model has been demonstrated through extensive experimentation to outperform AlexNet and VGG-19. The compared algorithms achieved accuracies of 88% for AlexNet and 93% for VGG-19, while the proposed H-FR model achieved 96%.

Keywords: Face Recognition; Hybrid Feature extraction; Machine learning; Lumination Normalization; Edge enhancement

1. Introduction

Facial feature recognition is an essential tool in computer vision, and it has several applications in security, biometrics, human-computer interaction, and entertainment [1]. As technology advances, ensuring data security has become crucial, particularly in sectors like national security, banking, e-commerce, and law, which require accurate personal identity verification. Biometric recognition based personal ID systems, which leverage unique biological characteristics that are nearly impossible to replicate, have gained prominence due to their enhanced security, validity, and dependability [2]. These systems are increasingly integrated into various aspects of daily life, with applications ranging from video surveillance and crowd analysis to behaviour analysis, teleconferencing, and personal identification through biometrics like [3], iris patterns [4], palmprints [5], DNA [6], and [7]. Face Recognition has become fundamental to the biometrics examination heading due to its ease in gathering face images, communicating many personal data characteristics, high Recognition, and originality [8-10]. Numerous algorithms and Strategies have been devised to enhance face recognition performance. Recent advances in image

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classification, such as face recognition, have effectively leveraged deep learning-based techniques to encode feature representations [11]. Deep learning (DL) can be employed in biometrics to discuss essential biometric information and make advancements when performed by multiple authentication and recognition systems [9]. Despite significant advances, achieving robust and accurate facial recognition in unconstrained environments remains challenging. Variations in pose and illumination conditions can significantly distort facial features, leading to decreased accuracy and reliability of recognition models [25-30].

Face recognition requires an effective combination of image processing techniques to improve the accuracy of edges and features, as well as advanced algorithms to accurately extract and match attributes [12]. Therefore, Illumination conditions significantly affect the visibility and appearance of facial features. This process enhances the contrast and visibility of facial features, ensuring consistency in their representation, regardless of the surrounding lighting conditions [31-34]. Moreover, for extraction of accurate image analysis, combine general or macro features (identifying larger objects, classifying/grouping, context, and color/ lighting) with fine or micro features (extracting details, identifying patterns/relationships). This hybrid feature extraction model patiently leads to comprehensive and in-depth image analysis [9, 11]. Facial recognition is a complex process that is influenced by various factors, such as environmental changes (lighting conditions) and facial emotion [9]. It can cause significant difficulties in how the face recognition models perceive and interpret facial features [1]. Moreover, when a face is rotated, or its position is changed, recognizing the facial features becomes even more challenging. The technical reason for this challenge is that the viewing angle changes, which requires advanced processing techniques to ensure accurate recognition [13]. Advantage techniques are required to ensure the accuracy and effectiveness of facial recognition in variance conditions.

To overcome face recognition challenges or mitigate the effects of uncontrolled environments on the face recognition model, we presented a new model that uses a hierarchical approach for facial feature extraction, ensuring robust performance despite dynamic changes in facial orientation and illumination conditions. In the first step, the model extracts coarse facial features before diving into the finer details, resulting in a comprehensive representation of the face. In addition, we use an illumination normalization technique specifically designed to handle different lighting conditions to improve the consistency and accuracy of feature extraction in different lighting conditions. Technically, the CLAHE is applied separately to the A and B channels of an image in LAB color space to enhance the edges and textures of an image. In addition, It improves the recognisability of detected features while normalizing the illumination of the image. The major aim of the proposed normalization is to avoid changing the image's brightness and complicating further analysis [11].

Data security is becoming increasingly important as computer and network technology advances [15]. Bioinformatics gives data more security than traditional methods, such as using passwords or pin codes. Face recognition has become fundamental to the biometrics examination heading due to its ease of gathering face images and communicating many personal data characteristics, high recognition, and originality [16]. It has seen a tremendous surge in interest owing to its potential to transform various applications. However, achieving high-precision recognition in real-world situations is complicated and has numerous challenges. The current. Face recognition models have some drawbacks that could be summarized as follows:

- **Lack of handling to illumination Variations**: Lighting conditions significantly affect facial recognition accuracy [16]. Varying illumination can distort facial features and cause shadows, which conventional models struggle to handle. The use of pre-train or deep learning to improve accuracy under changing light conditions
- **Low Accuracy in Feature Extraction**: Traditional facial recognition methods capture either broad or fine facial details, resulting in low accuracy, significantly when facial poses deviate from the norm [18].
- **Low accuracy with high complexity**: The details of the image with the facial emotion make a high difference at each capture, such as face emotion and variant luminance, which significantly affect the performance of the face recognition model [19]. Therefore, it is essential to ensure that the images used to train and test facial recognition models are diverse and represent the real-world conditions in which the models will be used. Adding more steps in pre-processing can increase the complexity of the model and may lead to overfitting, which can reduce the model's performance.

In facial recognition, the challenges posed by uncontrolled environmental conditions have long compromised the handle of different image orientations and dynamic processing, such as rotation and solid basis for hierarchical feature extraction techniques; they cannot account for the subtleties of dynamic illumination and pose variations. For this reason, we have developed a new model based on hierarchical feature extraction and adaptive illumination. The proposed model offers the following contributions:

- **Susceptibility to handling Illumination Variations**: The proposed model can effectively deal with variations in lighting within images by normalizing them through applying CLAHE techniques on separate channels of LAB (A and B). The proposed H-FR model produces normalized lighting across the image, enhancing the overall lighting quality of images.

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- **High correlation feature extraction**: The proposed feature extraction framework enables the proposed H-FR model to overcome the object orientation rotation and viewing angles. As a result, the proposed model can extract features that highly correlate to the image object, ultimately improving classification accuracy.
- **High accuracy and low complexity**: The empirical results show that the accuracy of the H-FR model has improved significantly. This is due to the ability to extract precise features, which are insensitive to illumination variations in the image. In addition, this model is less time and space-consuming

The proposed H-FR model was tested and evaluated over a dataset of 105 people's faces from Kaggle. Three evaluation strategies are used to prove the validity of the proposed model: quantitative, qualitative, and they are compared with recent face recognition models. The first strategy involves quantitatively comparing the model's results with those of other models. This uses metrics such as the Confusion Matrix, Accuracy, Precision, Recall, and the F1-Score. Additionally, performance is assessed in terms of time and required space resources. This comparison is made with modern deep learning algorithms like AlexNet and VGG-19. The second strategy is based on a qualitative comparison between the results obtained from the proposed model and the most recent models used in facial recognition. This considers the accuracy of facial discrimination and identification. These strategies comprehensively evaluate the model's performance in terms of numerical and qualitative metrics.

2. Related work

Since 1990, active research has been conducted in face recognition due to its many helpful applications. This study shows that landmarks obtained using a face recognition model are automatically transformed to mask a celebrity identity dataset. The face recognition model uses reconstructed faces as input to create feature embeddings.

Ali et al. [20] proposed a face recognition model based on deep learning and machine learning, such as SVM, KNN, and DT. Deep learning models process the input data through their layers, extracting complex patterns and high-level features. The output of this stage is a set of feature representations that effectively capture the essential information needed for recognition. The extracted features are then fed into a machine-learning model that classifies the data into predefined categories. Since the features are well defined and significant, the machine-learning model can make accurate predictions with relatively more straightforward functions. Despite the advantages of combining deep learning for feature extraction with machine learning for recognition, this two-stage approach can lead to complexities in the modeling process. It may be less flexible and adaptable to changes than a single integrated model. For example, suppose there is a change in the data distribution. In that case, retraining both the feature extraction and recognition models may be necessary, which increases the challenges and requires additional effort and resources.

Saib et al. [21] proposed several schemes for identifying masked faces. The main features of prominent faces were extracted using the Histogram Oriented Gradients method (HOG) and pre-trained models. Support Vector Machines (SVM) and a SoftMax layer are used as classifiers. They are using the HOG algorithm, as feature extraction does not address the luminance or the rotation problem, which can lead to inaccuracies in feature extraction, especially in face recognition. Therefore, the overall accuracy of the proposed model results in reduced precision and reality.

In [19], the authors demonstrated a Facial Emotion Recognition system (FER). It employed the (cascade regression tree) technique for feature extraction and compared the outcomes of machine learning algorithms for classification: KNN, SVM, and logistic regression. The limitation of this work is the use of SVM, which could be more efficient due to the high diminution problem.

The authors in [22] used VGG16 architecture in face recognition. They used a SoftMax classifier as the objective function. The proposed classifier's limitation is that it could be more efficient for low-quality images. Memory matching (a common problem) becomes problematic when too many classes exist. Due to its maximization of conditional probability, it matches high-quality images well. However, it does not consider the rare image from the training mini-batch.

Pournami et al. [23] proposed a system for missing child identification. The robust CNN based on DL for face features Extraction and the MSVM classifier for identifying various child classes are combined. This system is evaluated with the DL model, trained to depict features of children's faces. Removing the softmax from the VGGFace model to improve performance and extract CNN image features to train SVM. The proposed system performance is evaluated by utilizing images of children taken in different lighting and noise environments and images taken at various ages.

Usga et al. [24] introduced a study that used a (photo ID) as a dataset to determine the identification of a person. Age progression parameters for facial recognition systems are present in photo ID datasets using two types of datasets, namely (the primary for electronic identity cards and the tertiary IvS) datasets, to test the proposed technique. The core dataset comprises manually gathered information through questionnaires, whereas the second

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dataset is made available to the public. The authors only use one data for the training process: a photo ID that can only be used to recognize faces. As a result, they apply the pre-trained VGGFace2 model and (AM-Soft max loss) as a loss function to refine the data.

3. Material and method

This section explores the material and techniques used in the proposed model, "A Hybrid Intelligent Facial Recognition Model Based on Hierarchical Feature Extraction and Illumination Normalization “.

3.1. Dataset

The dataset used in evaluating the strategy of the proposed model is the Pins Face Recognition dataset. It is a curated collection of facial images designed to advance the capabilities of facial recognition systems. The dataset is available on the Kaggle repository at the web link:

https://www.kaggle.com/datasets/hereisburak/pins-face-recognition.

The dataset has thousands of images of 105 public figures and 17534 faces with varying facial expressions, angles, and lighting. It includes annotations for individual identification, facial landmarks, expressions, and bounding boxes. However, the dataset presents challenges, such as variations in illumination and partial occlusions, making it complex and requiring advanced algorithmic strategies. Figure 1 illustrates the samples of the Pins Face Recognition dataset.

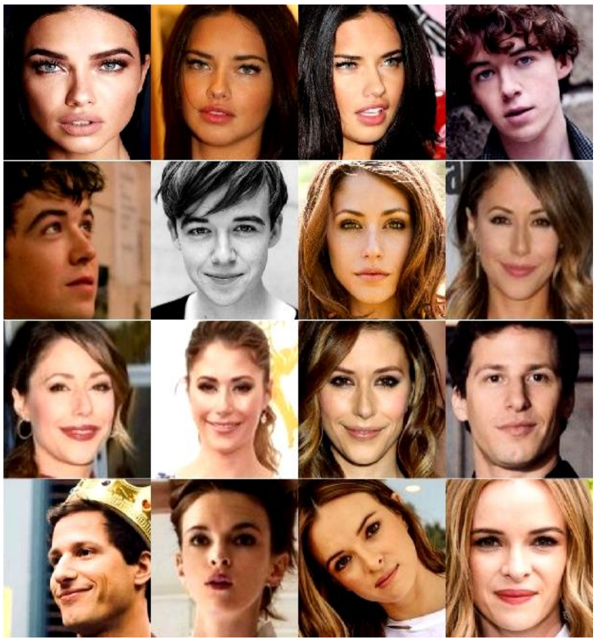

Figure 1. Sample from the Pins Faces Recognition dataset

3.2. Proposed H-FR model

For optimal performance, artificial intelligence algorithms necessitate images with distinctly clear features; this implies that edges must exhibit high contrast and that lighting should be uniformly consistent across all images to the greatest extent feasible. Technically, employing a singular filter to address both conditions is impossible due to the distinct requirements: edge enhancement necessitates a high-frequency filter, aligning with a high-pass filter (HPF). At the same time, lighting adjustments require a filter that accommodates lower frequencies; hence, a low-pass filter (LPF) is used. To achieve the desired goals of the proposed model in improving images and increasing accuracy in classification, the model can be divided into five main stages. Figure 2 illustrates the main steps of the proposed model.

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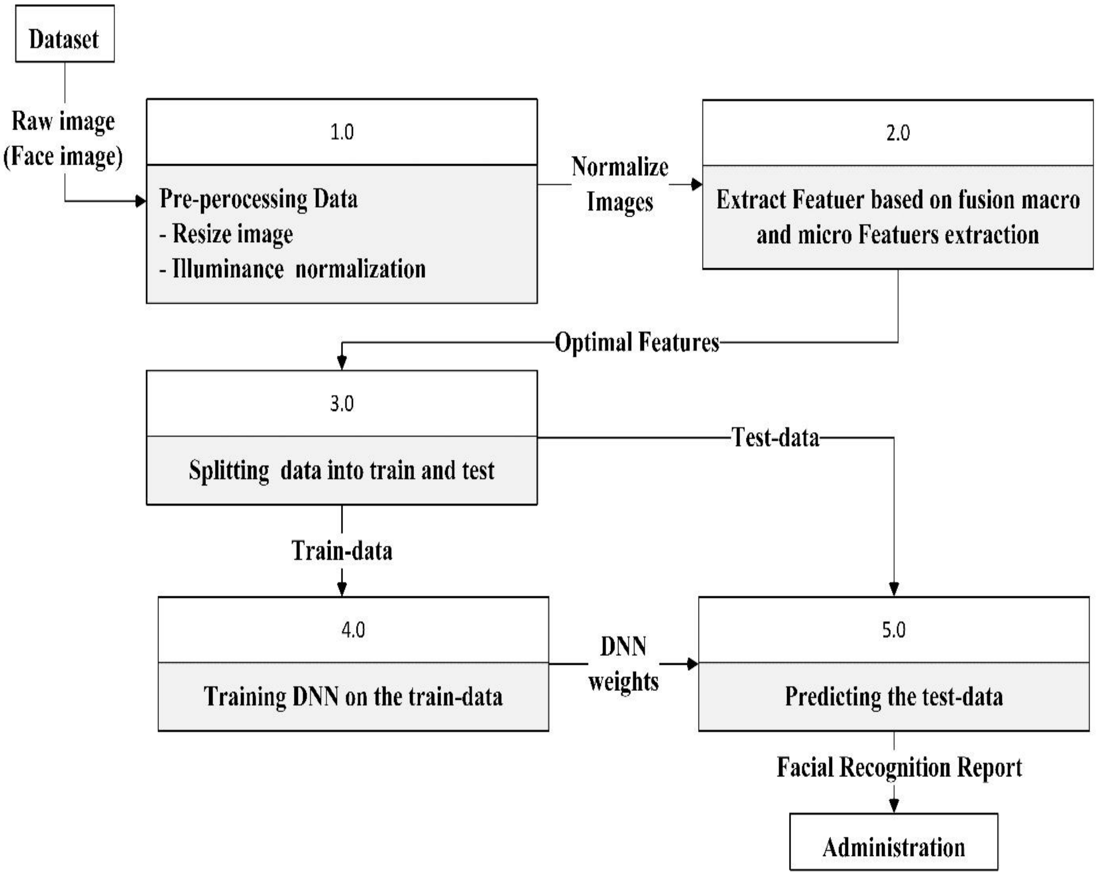

Figure 2. Main steps of the proposed H-FR

1. *Prepressing data*

In the pre-processing stage, the image is adapted to be suitable for the deep learning process. This stage includes equalizing the size and illuminances of the images so that they appear even and precise. The nearest neighbor's interpolation method standardizes the image dimensions to 100x100 pixels. This technique involves resizing the image by replicating pixels. It utilizes interpolation and resampling to achieve this transformation. In equation 1, the image $g(m, n)$ is generated from the original image $f(m, n)$ using a scaling factor c in the m direction and d in the n direction.

$$g(m,n) = \begin{cases} \frac{1}{cd}, -\frac{c}{2} \leq m < \frac{c}{2}, & -\frac{d}{2} \leq n < \frac{d}{2} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

According to [11], illuminance normalization can be achieved by converting the RGB image to LAB color space and applying contrast equalization (CLAHE) on channels A and B only "*without adjusting channel L*". The CLAHE aims to improve the contrast and independently enhance the features within each region, which can help in more consistent feature extraction under varying lighting conditions. Finally, the image with equalized color channels is reconstructed with the L channel.

Regarding image visualization (Figure 3), the proposed illuminance normalization method can evenly distribute the color over the entire histogram, resulting in more accurate edge detection and a more linear CDF. This ultimately improves the quality of the entire image. The effect of this illuminance normalization technique can be seen in the adjacent figure, which illustrates the impact on the input image.

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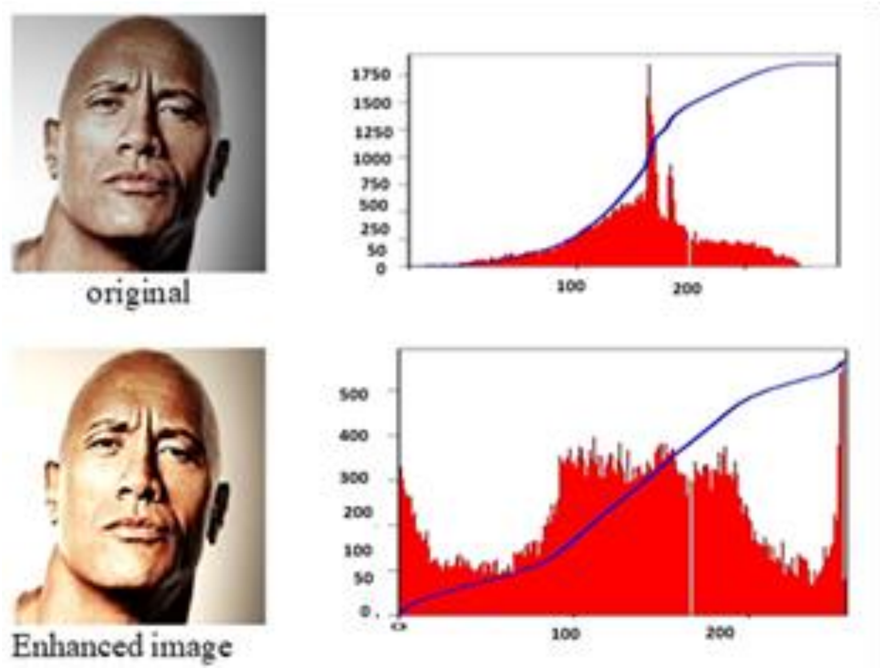

Figure 3. Effect of proposed illuminance normalization on the input image

Algorithm 1 shows how to normalize the illuminance of an image.

Algorithm 1*:* Image Illuminance Normalization

Input*:* input the BGR image (I)

Output*:* Enhanced _image (I_{LAB})

i. *I ← input the BGR image*

ii. *lab_image← BGR2LAB (I)*

iii. *L, A, B← extract_LAB component(lab_image)*

iv. *A_corrected ← CLAHE(A)*

v. *B_corrected ← CLAHE(B)*

vi. I_{LAB}*←Construct (L, A_corrected, B_corrected)*

Return I_{LAB}

2. Features extraction

The hierarchical feature extraction in the proposed model consists of three steps: extracting the macrofeature, the microfeature, and finally, a fusion of them. Technically, the proposed model used convolutional neural networks (CNNs) to extract macro and micro features from the pre-processed LAB image. Each CNN (CNN_{macro} and CNN_{micro}) comprises a series of convolutional layers, activation functions, pooling layers, and potentially fully connected layers. The mathematical formation of Hierarchical Features extraction is:

- **Extract Macrofeature** ($CNN_{\mathbf{macro}}$) : The macro feature extraction network captures the face's overall structure and coarse features. This convolution may consist of several layers. Equation 2,3 illustrates the mathematical formations of macro features (F_{macro}).

$$F_{\text{macro}}^{(1)} = \sigma\left(W_{\text{macro}}^{(1)} * I_{LAB} + b_{\text{macro}}^{(1)}\right) \tag{2}$$

$$F_{\text{macro}}^{(i)} = \sigma\left(W_{\text{macro}}^{(i)} * F_{\text{macro}}^{(i-1)} + b_{\text{macro}}^{(i)}\right) \tag{3}$$

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- **Extract Microfeature** ($\boldsymbol{CNN}_{\mathbf{micro}}$): The microfeature extraction network focuses on capturing finer details, such as textures and small-scale features. Its formulation would be similar to the macro network but with possibly smaller filters and more profound architecture to capture high-resolution. Equation 4,5 illustrates the mathematical formations of micro features (F_{micro})

$$F_{\text{micro}}^{(1)} = \sigma\left(W_{\text{micro}}^{(1)} * I_{LAB} + b_{\text{micro}}^{(1)}\right) \tag{4}$$

$$F_{\text{micro}}^{(i)} = \sigma\left(W_{\text{micro}}^{(i)} * F_{\text{micro}}^{(i-1)} + b_{\text{micro}}^{(i)}\right) \tag{5}$$

Where: is the number of layers in the microfeature extraction network and other symbols that have analogous meanings to those in the macro network.

- **Pooling Layers**:

Pooling layers reduce the dimensionality of the feature maps, decreasing the computational load and helping achieve translational invariance. Function 6 finds the final features of both microfeatures and macrofeatures.

$$P_{\text{macro}}^{(i)}(x, y) = \max_{(a,b)\in W_p} F_{\text{macro}}^{(i)}(x \cdot s + a, y \cdot s + b) \tag{6}$$

Where: W_p is the window of the pooling operation and s is the stride.

- **Feature Fusion**: This step combines macro and microfeatures using a fusion operation. It allows the proposed model to learn from both the macro and micro perspectives. Technically, proper fusion leads to more accurate pattern recognition. Concatenation was used as a fusion form to reduce the proposed H-FR's complexity. Equation 7 illustrates the fusion_concatenation.

$$F_{\text{combined}} = [F_{\text{macro}} ; F_{\text{micro}}] \tag{7}$$

3. Splitting data into train and test

In machine learning, data is typically split into training and testing sets to accurately evaluate the model's performance. For the proposed model, a 70% train and 30% test split ensure substantial data for training while retaining enough unique data points for effective model validation. This approach assesses the model's applicability and avoids overfitting issues, where a model performs well on training data but poorly on unseen data.

4. Training by DNN on the train data and prediction

The proposed H_RF model uses the Deep Neural Network (DNN) as an objective function for the recognition of faces It trains with five fully connected dense layers of train data. It involves a structured process where each layer's neurons are interconnected, facilitating learning complex patterns from the data. During the training phase, which utilizes 70% of the data, the network undergoes iterative adjustments of weights and biases through forward and backward propagation, employing optimization techniques like stochastic gradient descent. The remaining 30% of the data evaluates the model's performance.

4. Experiment result

This section analyses the results model and tests the validity of the proposed H-FR. Technically, the proposed model consists of two parts: the first part is for illumination enhancement, and the second is for face recognition. We have compared the model with an algorithm using light image enhancement techniques. As for the second part, the model was compared with two deep learning algorithms, AlexNet and VGG 19; the model was also tested in dealing with overfitting problems in the training phase.

4.1. Evaluation of the Illuminance Normalization:

No-reference Image Quality Assessment (NR-IQA) is crucial for evaluating image quality in varying light conditions without needing a reference image. This is particularly relevant as digital images often degrade due to storage, compression, transmission, or environmental factors like poor lighting. Typically, human evaluation is the most accurate method for assessing image quality, but it's not feasible for real-time systems due to its high cost and time constraints. To evaluate the first part of the proposed H-FR model," *illuminance normalization (I_LAB),*" we used objective and subjective evaluation. In the objective evaluation, five NR-IQA metrics are factors e, σ, average r, Naturalness Image Quality Evaluator (NIQE), peak signal-to-noise ratio (PSNR) – for more information about the NR-IQA see references [13,30].

Table 1 compares our proposed illuminance normalization technique with the standard Histogram Equalization (HE) and CLAHE methods. In this analysis, these standard methods were applied to RGB images. This comparison

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was conducted over 10 randomly selected images with low-light conditions to find the average value of NR-IQA. The table aims to highlight the effectiveness of our approach in enhancing image quality under such challenging low-illuminance scenarios.

Table 1: Comparative evaluation of illuminance normalization technique

Model	e↑	σ↑	r↑	PSNR↑	NIQE↓
HE	2.6	2.76	0.18	20.73	5.17
CLAHE	4.35	5.3	0.28	21.15	4.52
I_LAB	5.98	6.07	0.42	24.09	3.81

Accurately defining the shapes and intricacies within images is crucial for distinguishing various objects depicted within them. The proposed model has successfully attained a high level of precision in enhancing image edges while maintaining uniform lighting distribution, leading to increased accuracy in outcomes, as evidenced in the initial Table 1. The table demonstrates the advancements of the I_LAB model in enhancing image quality, particularly in low-light conditions, making it a preferable choice in NR-IQA applications.

Based on observation, the proposed I_LAB model provides significantly clearer images than the other two techniques. One reason for this is the enhanced visibility of facial features, a crucial aspect of image processing. Additionally, the lighting in the images appears to be more evenly balanced, resulting in an overall better-quality image output.

Figure 4. Comparative of light enhancement of HE, CLAHE and I-LAB on Pins Faces Recognition dataset

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4.2. Comparison with Deep Learning Algorithms:

Before testing the accuracy of the proposed face recognition model and the deep learning algorithms VGG19 and AlexNet, we need to test the proposed model's ability to handle overfitting in the training phase. Figures 5, 6, and 7 show the progress in training for the proposed H-FR, VGG19, and AlexNet, respectively.

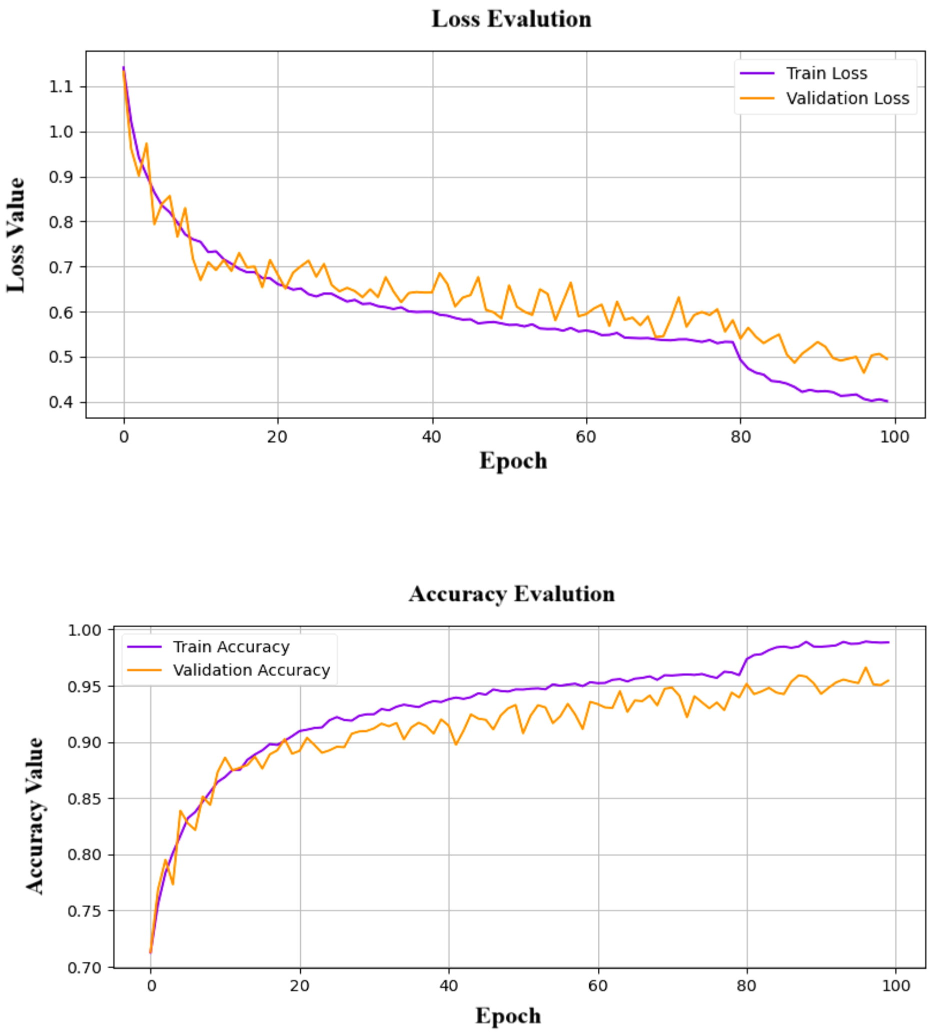
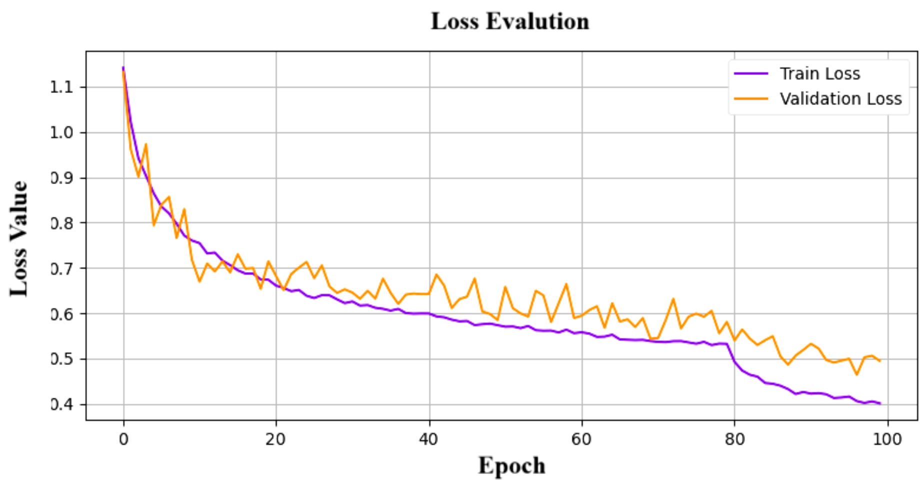


Figure 5. Train phase of proposed H-FR over 100 epochs



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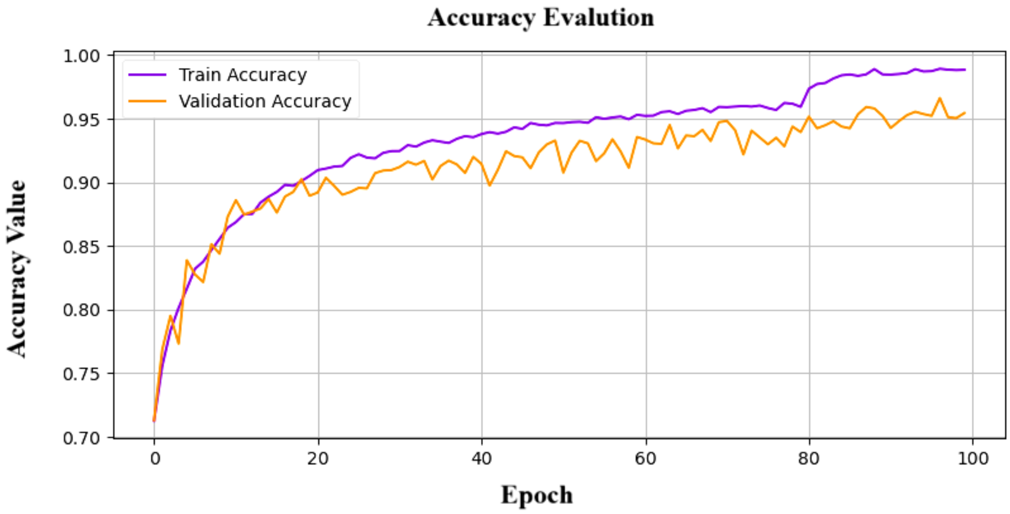

Figure 6. Train phase of proposed VGG19 over 100 epochs

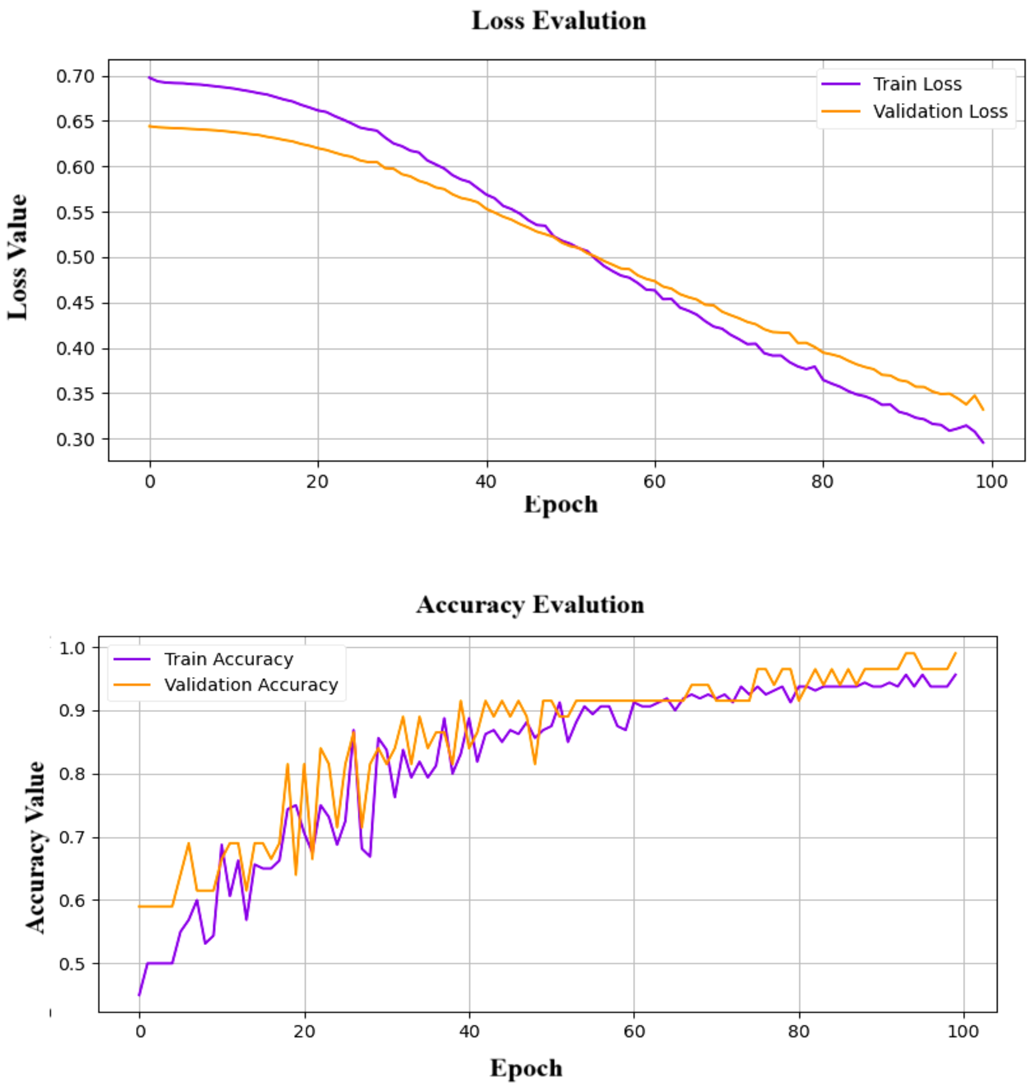

Figure 7. Train phase of proposed AlexNet over 100 epochs

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The figures above (5,6 and 7) show that the proposed H-FR model achieves good results in coping with the training phases and with less overfitting. At the same time, the VGG-19 algorithm suffered from overfitting in the final stages of training, indicating that it used many complexifications, which caused it to fall into overfitting. On the other hand, the probability of an overfitting event increased in the training phases; on the other hand, the algorithm did not suffer from overfitting.

Analyzing the training phase is insufficient proof that the algorithm has achieved good results, but we need to test it on new data and its classification ability. Including the training phase in the comparison does not hurt, as machine learning and deep algorithms depend heavily on the training phase. The accuracy face recognition of the proposed and established algorithms VGG19 and AlexNet is used in the test validity and performance of the proposed H-RF model. The comparison is based on four evaluation metrics: accuracy, precision, recall, and F1-score. Table 2 compares the H-FR results with two deep-learning algorithms, VGG-19 and AlexNet. The proposed algorithm had a reception rate of 96. VGG-19 had a rate of 93%, and AlexNet was 82%. Because of meticulous training and appropriate techniques in the working environment to minimize overfitting, the proposed model shows high accuracy in facial recognition and is adaptable to potential variations in data. The proposed model achieves a high F1-score compared to comparative algorithms (VGG-19 and AlexNet), reaching 97.22%. A high F1 score may indicate that H-FR uses a more advanced algorithm or trains on a more diverse dataset, possibly with sophisticated regularization strategies, improved treatment of imbalances in the data, or fine-tuned thresholding strategies that balance precision and recall.

4.3. Compare with other studies

Table 3 compares the proposed face recognition model to three other models. Model [19] achieved a 94.87% accuracy by utilizing deep feature extraction and machine learning classification algorithms, indicating a layered approach progressing from general to specific pattern recognition. Model [32] achieved a slightly higher accuracy of 95.29% by leveraging YOLOv5 and GANs to reconstruct obscured facial features, which is especially beneficial in identifying individuals wearing masks. Model [24] attained an accuracy of 93.51% by relying on pre-trained deep learning models, which may streamline the recognition process but could be less effective in handling the variability of real-world identity verification. The authors in [33] achieved an accuracy 90.93 in face recognition. The proposed H-FR model achieved the highest accuracy of 96.45% due to its advanced methodological framework, which probably includes a more comprehensive and adaptive feature extraction approach. This could be achieved through a dynamic neural network architecture fine-tuned or specifically designed to cope with the age, facial expression, and occlusion variations encountered in e-ID verification. Additionally, H-FR's success can be attributed to a training regimen that includes data, which ensures robustness and mitigates overfitting, leading to high precision in pattern recognition and generalization to new situations.

Table 2: Comparative Performance Metrics of H-FR, VGG-19, and AlexNet Algorithms

Model	Precision	Recall	F1-score	Accuracy
AlexNet	92.18	84.14	87.98	88.09
VGG-19	93.28	94.16	92.21	93.81
H-FR	**98.08%**	**96.38%**	**97.22%**	**96.45**

The models based on deep learning are based on two fundamental parts: The first is the accuracy of feature extraction, and the second is the strategy for predicting these features. The clearer and higher resolution the targets in the image are, the more efficient the extracted features are. Therefore, data preparation before feature extraction is necessary to increase the learning accuracy of deep learning algorithms. On the other hand, uneven illumination in the image has a negative effect on the clarity of the objects, which reduces the performance of the algorithm. In the proposed model, we have used an algorithm that normalizes the illumination to distribute it more evenly over parts of the image, which improves the accuracy of the subjects and sharpens the edges. Our feature extraction strategy is based on two stages: the first for extracting general features, such as illumination, and the second for extracting fine features, such as the texture of the image. Thus, the proposed model outperforms other deep learning algorithm models thanks to data initialization and fine-grained feature extraction, which improves the accuracy of distinguishing targets in the image.

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5. Conclusion

Facial recognition is essential for biometrics, security, and human-computer interaction. Achieving accurate results under different environmental conditions can be difficult. Traditional and modern face recognition models struggle with illumination changes and pose variations in real-world scenarios. A new model combines hierarchical feature extraction with illumination normalization to solve these problems. The goal is to make recognition more reliable under different conditions. It uses Adaptive Histogram Equalization in the LAB colour space to improve the visibility of facial features. It combines macro and micro features to increase accuracy and correlation. Using hierarchical feature extraction and illumination normalization, the proposed face recognition model is significantly more accurate than two deep learning models (AlexNet and VGG-19). The proposed model achieved an accuracy of 96.45% on the Pins Face Recognition dataset. In future research, integrating 3D modeling and deep learning techniques could further improve the robustness of the model to more complex variations in facial pose and occlusions.

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