CHAPTER 2
LITERATURE SURVEY

2.1 INTRODUCTION

The applications of the face recognition system are tremendously increasing in day-to-day life. The accuracy of face recognition system is highly important especially in the field of surveillance, access control and law enforcement applications. Face recognition system struggles to recognize faces affected by illumination [5, 21]. One of the key challenges of face recognition system is to bring out facial features necessary for recognition despite variation in illumination [17]. There is an interesting compendium of literature in the area of illumination enhancement techniques and face recognition techniques. This chapter discusses the methodology and features of various illumination enhancement techniques and face recognition techniques available in the literature. The tree structure depicting the hierarchy of illumination pre-processing techniques is shown in Figure 2.1.

2.2 ILLUMINATION PRE-PROCESSING TECHNIQUES

Illumination Pre-processing techniques are broadly classified into three main categories [5]. They are namely:

- Gray Level Transformation Technique
- Gradient Edge Detection Technique
- Reflectance Field Estimation Technique

2.3 GRAY LEVEL TRANSFORMATION TECHNIQUE

Illumination enhancement using Gray Level Transformation Technique maps a pixel of the input image to an intensity value obtained using a transformation function. The transformation function aims to redistribute the intensity value in the image, which results in an enhanced
Figure 2.1 Tree Structure of Illumination Pre-processing Techniques

Illumination Pre-processing Techniques

Gray Level Transformation Technique
- Histogram Equalization
- Gamma Intensity Correction
- Logarithmic Transformation (LT)

Gradient Edge Detection Technique
- Directional Grey-scale Derivative
- Laplacian of Gaussian
- Single-Scale Retinex
- Gaussian high-pass

Reflectance Field Estimation Technique
- Self-quotient image (SQI)
- Logarithmic Discrete Cosine Transform (LDCT)
- Logarithmic Total Variation (LTV)
- Local Normalization (LN)

- Local Histogram Equalization (LHE)
- Partial Overlapped Histogram Equalization (POSHE)
- Brightness preserving Bi-Histogram Equalization (BBHE)
- Dualistic Sub-Image Histogram Equalization (DSIHE)
- Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)
- Recursive Mean Separate Histogram Equalization (RMSHE)
- Recursive Sub Image Histogram Equalization (RSIHE)
- Dynamic Histogram Equalization (DHE)
- Brightness Preserving Dynamic Histogram Equalization (BPDHE)
- Histogram Equalization using Neighbourhood Voting Metric (VM)
- Histogram Equalization using Contrast Difference Metric
- Histogram Equalization using Distinction Metric
image compared to the original image. The Gray Level Transformation techniques are:

- Histogram Equalization (HE) Technique
- Gamma Intensity Correction (GIC) Technique and
- Logarithmic Transformation (LT) Technique.

2.4 HISTOGRAM EQUALIZATION TECHNIQUE

Histogram Equalization (HE) Technique is also called the Global Histogram Equalization (GHE) Technique. It is most simple, efficient and effective contrast enhancement technique suitable for almost all types of images [18]. GHE increases the overall contrast of an image. In GHE, the transformation function is defined using the cumulative probability density function to redistribute the input image gray levels values [19]. The transformation function used in GHE is obtained using the whole input image [18,19]. GHE flattens and stretches the dynamic range of the image's histogram, which results in an overall contrast-enhanced image [18, 19, 20]. The ideal contrast-enhanced image histogram is perfectly flat and makes use of every gray value in the image format [18]. However, in practical scenario GHE exhibits some drawbacks. One of the drawbacks of histogram equalization technique is, histograms resulting after applying GHE contains gaps (i.e. there are empty bins) [18, 20]. Also, large bins present in the input image have not been subdivided, rather they are only spread out [18, 20].

2.4.1 Local Histogram Equalization Technique

Local Histogram Equalization (LHE) Technique has been developed to overcome the drawbacks of GHE [5, 18]. In LHE, a mask of size 3 x 3 is defined and histogram equalization function is determined for that region. The centre pixel of 3 x 3 masked region is equalized using this function. The mask is moved to have the next adjacent pixel as the centre pixel. Again, the same procedure is repeated to equalize the centre pixel value. This process is carried out for the entire image. LHE produces a highly contrast image but the image is over enhanced [5, 18, 19]. This method also
requires more computation as histograms are constructed and equalized for each pixel in the image [18, 19].

2.4.2 Other Extension of GHE

Over the years many research works have focused on improving GHE further and some of them are as follows

- Brightness preserving Bi-Histogram Equalization (BBHE)
- Dualistic Sub-Image Histogram Equalization (DSIHE)
- Minimum Mean Brightness Error Bi-Histogram Equalization (MMEBHE)
- Recursive Mean Separate Histogram Equalization (RMSHE)
- Recursive Sub Image Histogram Equalization (RSIHE)
- Dynamic Histogram Equalization (DHE)
- Brightness Preserving Dynamic Histogram Equalization (BPDHE)
- Histogram Equalization using Neighbourhood Voting Metric (VM)
- Histogram Equalization using Contrast Difference Metric
- Histogram Equalization using Distinction Metric

2.4.2.1 Brightness preserving Bi-Histogram Equalization (BBHE)

Histogram Equalization Technique does not preserve the brightness of the original image. There are few applications where retention of original brightness of the image is essential. Bi-Histogram Equalization was proposed to preserve the brightness of the input image [23, 24]. In BBHE, as the first step, histograms for the input image is obtained. Then mean value of the histograms is computed. This mean is used to divide the image histogram into two different subgroups of histograms[23]. Then each subgroup of histograms is equalized independently. It has been proved mathematically and experimentally that BBHE is capable of maintaining the original brightness of the image to certain extent [23, 24].
2.4.2.2 Dualistic Sub-Image Histogram Equalization (DSIHE)

DSIHE is another approach taken to preserve the brightness of the original image. In DSIHE, histograms for the input image are computed. The median value of the histograms is computed. This median is used to divide the image histogram into two different subgroups of histograms [25]. Then equalization is done between the lowest intensity values present in the image format to median separately and again equalization is done between the median value of the input image to the highest intensity value present in the image format. This method claims to outperform BBHE both in terms of maintaining the brightness and image entropy [25, 26].

2.4.2.3 Minimum Mean Brightness Error Bi-Histogram Equalization (MMEBE-BHE)

BBHE operates using the mean of the input image as the threshold for dividing the input image histograms [23, 24]. The brightness of the image is preserved to a great extent when using the mean of the input image for separation of the input image histograms. This is measured using the objective measure, namely Absolute Mean Brightness Error (AMBE) which is defined as the difference between the mean of input and output images. If the AMBE value is lower, it implies that there is better brightness preservation. Hence, the threshold used to divide the input histogram should be based on AMBE value. More than one threshold value is taken and among them, the one that yields lesser AMBE value is taken as the mean based on which the input histograms will be divided into two subgroup of histograms [24]. After separation, each sub histogram is equalized independently.

2.4.2.4 Recursive Mean Separate Histogram Equalization (RMSHE)

BBHE divides the input image’s histogram into two subgroups histograms based on its mean and then equalizes them independently [23]. In BBHE, the separation is done only once. In RMSHE, the separation is performed recursively [27]. In RMSHE, initially, the image histograms are divided into two subgroups using the mean value of the image. Each new
subgroup of histograms is again separated using their respective means recursively [27]. It is analyzed mathematically that the output image's mean brightness will converge to the input image's mean brightness as the number of recursive mean separation increases [23, 27]. The convergence of the mean of the input image with the mean of the output image reveals that AMBE value will be almost zero. This implies that the brightness of the original image is preserved to a large extent. RMSHE claims to outperform HE, BBHE and Dualistic Sub Image Histogram Equalization (DSIHE) in preserving the brightness of the output image [27].

2.4.2.5 Recursive Sub Image Histogram Equalization (RSIHE)

In RSIHE, the cumulative probability density is used to separate the histograms of the input image [28, 29]. The gray level value for which the cumulative probability density function is equal to 0.5 is used to divide the image into two sub-images (\(W_L\) and \(W_U\)) where \(W_L\) is the sub-image less than the chosen gray level value for subdivision and \(W_U\) is the sub-image higher than the chosen gray level value[28, 29]. Now each sub-image is equalized independently[30, 31]. After equalizing the sub-images, they are combined to form the equalized full image[28, 29, 30, 31].

2.4.2.6 Dynamic Histogram Equalization (DHE)

In Dynamic Histogram Equalization, the histograms of the image are partitioned using local minima [32]. Suppose \(m_0, m_1, m_2, \ldots, m_n\) are the local minima in the image histogram, the first partition consists of histogram between the range \(m_0\) and \(m_1\). Similarly, next partition consists of histogram between \(m_1\) and \(m_2\). Each of these partitions or sub histograms are equalized between the span of gray level allocated by DHE [32]. The advantage of equalizing between the dynamic range results in increasing the spread of the histograms and to avoid the domination of some parts of the histograms over the other.
2.4.2.7 Brightness Preserving Dynamic Histogram Equalization (BPDHE)

Brightness Preserving Dynamic Histogram Equalization is an extension of DHE [33]. DHE did not concentrate to maintain the brightness of the input image [32]. In BPDHE, the initial step is to partition the image histogram into subgroups of the histogram using the local maxima. After partitioning the image, each partition is equalized independently between the dynamic ranges. After equalization of each partition, the brightness of the image is normalized [32]. This helps to retain the brightness of the input image. The main advantage of BPDHE is the presence of the advantages of DHE along with brightness preservation [33].

2.4.2.8 Histogram Equalization using Neighbourhood Voting Metric (VM)

Histogram Equalization using Voting Metric considers both the local and global information in the image [18]. The main drawback of histogram equalization technique is the existence of large bins and gap between the bins even after equalizing the illumination affected image [18, 20]. To overcome this drawback voting metric was introduced. In voting metric, a neighbourhood of size $3 \times 3$ is initially defined. The vote represents the number of neighbours strictly less than the centre pixel. For the same centre pixel intensity value, vote from the neighbours is obtained from the whole input image. This measure helps to divide the large histograms bins into eight sub bins [18, 20]. Now when equalization is done, each sub bin is mapped to a different intensity value in the output image.

2.4.2.9 Histogram Equalization using Contrast Difference Metric

Histogram Equalization using Contrast Difference Metric also considers both the local and global information in the image. In voting metric large histogram bins of the image are divided into eight sub bins. These eight sub bins are obtained by considering only the neighbourhood pixels less than the centre pixel[18]. In Contrast Difference metric large histogram bins of the image are divided into twenty seven sub bins [34, 35]. In contrast difference
metric, a neighbourhood of size 3x3 is defined. The contrast difference metric is computed by considering the count of neighbours less than the centre pixel value and the count of neighbours greater than the centre pixel value. In this way, each large histogram bin is subdivided into twenty seven sub bins [34, 35]. After the subdivision, histogram equalization is performed. This increases the spread of histograms in the resultant image.

2.4.2.10 Histogram Equalization using Distinction Metric

Histogram equalization using Distinction Metric aims to increase the flatness of the histograms [20]. Large bins are divided into more number of sub bins compared to voting metric and contrast difference metric. In distinction metric 3x3 mask is initially considered. The distinction metric is the summation of the difference between the centre pixel and the neighbouring pixels less than the centre pixel. The distinction metric is obtained for each occurrence of particular intensity value. Each bin is divided into sub bins by grouping them using the distinction value. Pixels with similar distinction value are grouped in sub bin. After this histogram equalization is performed and each sub bin in the histogram bin is mapped to a different value. This increases the overall contrast of the image [20]. Uniform distribution of histogram results in high contrast image [18, 20, 34].

2.5 GAMMA INTENSITY CORRECTION (GIC)

Gamma Intensity Correction controls the brightness of the image by changing the gamma value [36, 37]. Gamma correction can also be thought of as the process of compensation for the non-linearity in order to achieve correct reproduction of intensity [36, 37, 38]. In Gamma intensity correction, a predefined face image (say I₀) which is lighted under normal condition is first considered. Then the face image (say I) captured under defective lightening condition is considered. GIC aims to change the overall brightness of the input images I to best fit the brightness of the pre-defined normal face images I₀ [36]. Thus, the effect of GIC is that the overall brightness of the illumination affected face images is adjusted to the same level as that of the predefined face image I₀ [36, 37].
2.6 LOGARITHMIC TRANSFORMATION (LT)

Logarithmic Transformation maps non-linearly the pixel intensities and as a result, the shadowed regions will be enhanced producing a resultant image with more clarity in the low-illumination regions [39]. Logarithmic transformations enhance low gray levels and compress the high ones [39, 40]. They are useful for non-uniform illumination distribution and shadowed images. However, they are not effective for high bright images [39, 40, 41].

2.7 GRADIENT EDGE DETECTION TECHNIQUE

One of the basic and most important features of an image is the edges of the image [42, 43]. Edges are illumination invariant features that are used by the visual system to recognize objects [42]. Edge information helps the user to understand the structure of the face. The composition of the edges helps us to understand the object structure. The image representation in edge-based model is like an artist line drawing, where the lines mark the key surface shapes and material feature on the face [42, 43].

Gradient or Edge extraction methods calculate gradients of a face image. The gradient of the face image is illumination-insensitive representation. Gradients are steadier than the pixel intensities, which vary under different lighting conditions [42, 43].

Few examples of Gradient extraction methods are as follows

- Directional Grey-scale Derivative (DGD),
- Laplacian of Gaussian (LoG)
- Single-Scale Retinex (SSR)
- Gaussian High-Pass (GHP)

Directional derivative extracts edge information of an image [44]. Directional Grey-Scale Derivative (DGD) shows the directional change in the intensity values of the image [44]. The derivative at a point on the image is a two-dimensional vector in the horizontal and vertical directions [5]. At each point in the image, the derivative vector points in the direction of largest possible intensity increase, and the length of the derivative vector corresponds to the rate of change in that direction.
The Laplace image enhancement algorithm is used for enhancing the details of an image [45]. Laplacian of an image computes the second spatial derivative of an image [5]. It is useful in detecting abrupt changes [45]. In Laplacian of Gaussian, smoothing is performed using Gaussian filter prior to Laplacian as it is useful for the removal of noise present in the image [45].

Single Scale Retinex method is based on human observations. The Retinex is an image enhancement algorithm, which is used to improve the contrast, brightness and perceived sharpness of images. The algorithm also simultaneously provides the colour constant output, which removes the effects caused by different illumination on a scene [46]. Single Scale Retinex method bridges the gap between actual images and the human observations of scenes.

Gaussian high pass filter detects the edges in the image which are illumination invariant information [47]. The major function of the high-pass filter is to mitigate and eliminate energy of low frequencies within the image as well as accentuate edges and details of the image [45, 47]. This information is vital for recognizing faces across illumination variation.

Gradient edge detection techniques extract edges and gradient from face images but are still affected by shadows [5].

2.8 REFLECTION FIELD ESTIMATION

The Reflection Field Estimation model estimates the face reflectance field, which is illumination invariant. This method uses the reflectance-illumination model, which represents the face as a product of face reflectance and illumination component. Some of the methods that fall under the category of Reflection field estimation technique are as follows:

- Self-Quotient Image (SQI),
- Logarithmic Discrete Cosine Transform (LDCT),
- Logarithmic Total Variation (LTV),
- Local Normalization (LN)
2.8.1 Self-Quotient Image

The Self-Quotient image of a face image reveals the intrinsic properties of the face image considered [48, 49]. The point wise division of the given image with the smoothed version of the input image computes SQI of a given image. The SQI images are good at removal of shadows [48].

2.8.2 Logarithmic Discrete Cosine Transform

Logarithm transform is used in image enhancement to expand the values of dark pixels [50]. The image gray level f(x,y) can be represented as the product of the reflectance r(x, y) and the illumination i(x,y). The reflectance component of an image contains the stable characteristic of facial features. Taking logarithms helps to recover the reflectance component of the face image. Since illumination variations mainly lie in the low-frequency band, we can approximately estimate them using the low-frequency DCT basis images and their corresponding coefficients [50]. The facial features in the dark area of the original image are recovered much better by applying DCT on the logarithm image [50].

2.8.3 Logarithmic Total Variation

The LTV model factorizes a single face image into the illumination dependent component and an illumination-invariant component [51, 52]. Facial Structure is the illumination invariant component used for face recognition. The LTV extracts only the illumination invariant small intrinsic facial features for recognition. The intrinsic structures which are in general on a smaller scale than extrinsic illumination artifacts and shadows contributes to face recognition [51, 52]. LTV works on the assumption that for face recognition purposes, small scale facial structures may be the key to frontal face recognition [51]. LTV depends on the selection of a parameter $\lambda$ (lambda) which separates the facial structures into small scale and large scale features. The choice of lambda depends on the size of the face images [52]. Hence, the choice of $\lambda$ is of paramount importance in achieving good performance of LTV.
2.8.4 Local Normalization (LN)

Local Normalization effectively and efficiently gets rid of the uneven effects of illumination variation while keeping the local properties of the processed image the same as the corresponding image under good lighting conditions [53]. The main assumption in Local Normalization is that a human face can be divided into small and flat facets. After dividing the human face into small and flat facets, Local Normalization is applied for each facet. Local Normalization is proposed with the concept of having local mean to be equal to zero and the variance to be equal to one within all facet of the given face image [53].

2.9 COMPARATIVE ANALYSIS

HE, LT and GIC Techniques do not completely eliminate the shadows present in the illumination affected face images [5]. DGD and LoG techniques extract the edges or gradients from face images, which are robust to intensity variation, but face images are affected by severe shadows [5]. SSR, GHP, LDCT, LTV and LN techniques enhance facial features for both the regions with ideal lighting and shadows but they may also enlarge the photon or sensor noises [5]. In comparing the three methodologies, namely Gray Level Transformation Techniques, Gradient Edge Detection Techniques, and Reflectance Field Estimation Techniques literature reveals that Gray Level Transformation and Reflectance Field Estimation techniques preserve more facial features compared with Gradient or Edge Extraction based methods [5]. In comparing Gray Level Transformation with Reflectance Field Estimation techniques, Gray Level Transformation Techniques are simple techniques which take less computational time as they work in the spatial domain. Also, the literature clearly shows that Global Histogram Equalization which is a Gray Level Transformation technique can be extended to local patches to enhance its performance [5].

2.10 BACKGROUND OF FACE RECOGNITION

Face recognition has gained paramount importance in the recent years of research as it has the huge impact in the field of security and
surveillance. Changes in illumination condition cause variation in the appearance of face images. These face images degrade the performance of face recognition system [5, 48, 49, 50, 51, 52, 53, 54].

Some of the well-known face recognition methods are:

- Correlation-based methods
- Principal Component Analysis (PCA) Method
- Linear Binary Pattern (LBP)
- Local Ensemble Classifier (LEC)

2.10.1 Correlation-based methods

Correlation based methods are the simplest among the various face recognition techniques [55]. They are based on nearest neighbourhood classifier. In this method, the test image is recognized or classified by assigning it to the class of the closest face image in the learning set, where distances are measured in the image space [55]. The images in the training face are normalized to have zero mean and unit variance. Thus, normalization and grouping help to assign the best matches in the database. The major disadvantage of the Correlation based method is that if the images in the learning set and test set are congregated under different lighting conditions, then the subsequent points in the image space may not be tightly clustered. Correlation is a computationally extensive task and with respect to the recognition and test face has to be correlated with all the images in the database. Correlation-based methods yield 45.2% of recognition rates on Yale B Extended Face Database [5].

2.10.2 Principal Component Analysis (PCA) Method

PCA is also called Eigenfaces method. In the Eigenfaces or Eigenvectors approach, the main concept is to characterize or capture the variation between the face images in the database [56, 57]. PCA is a holistic or a global technique. Mathematically these Eigenfaces are called the principal components which are ordered based on the significance of the corresponding Eigenvalues. For a database with \( n \) number of faces, \( n \) number of Eigenvectors are generated. All Eigenvectors obtained are not
used in the recognition process [58]. The most significant Eigenvectors corresponding to large Eigenvalues are used in the recognition process. As the face is high dimensional space, Eigenface introduces the concept of dimensionality reduction [59].

The weight vector for each input image is estimated by projecting the training images on the face space (set of most significant Eigenfaces). The test image is given as input to the system, the test image is also projected in the face space and weight vectors are estimated. The distance measure between the weight vector of the test face and the set of known faces are determined. The weight vector of known face corresponding to minimum distance is identified to be the best match for the test face image. PCA yields 31.4% of recognition accuracy on Yale B Extended Face Database [5].

To improve the face recognition accuracy of face images with variation in expression PCA was further enhanced to two different approaches, namely

- Modular Principal Component Analysis (MPCA),
- Two-dimensional Modular Principal Component Analysis (2DMPCA).

2.10.2.1 Modular Principal Component Analysis (MPCA)

Modular PCA method is an extension of the PCA method used for face recognition [58]. This modular PCA method achieves better results than the PCA method in recognizing face images subjected to variation in expression and illumination [58, 59]. Modular PCA does not contribute significantly towards recognition of face images subjected to variation in pose. Hence face recognition system can use modular PCA as a substitute to PCA where there are possibilities of acquiring real-time face images subjected to variation in expressions [58].

Variations in the expression affect only certain parts of the face image and the remaining parts of the face image remain the same as a normal face image. In modular PCA the faces in the training set are
modularized into small images. As in PCA, all the steps are repeated to calculate the weight vector of the training face set.

2.10.2.2 Modular Image PCA (IMPCA) or Two-Dimensional PCA

The Image/two-dimensional PCA approach (2DPCA or IMPCA) extracts features from the face image matrix [60,61]. In one dimensional PCA or classical PCA, the face image is transformed into one-dimensional vector. In 2DPCA [61], the covariance matrix is constructed using original image matrix. The direct usage of original image matrix for application of PCA significantly reduces the calculation. Modularization of image decomposes a face image into different face regions. Hence, if a part of the face is affected by illumination variation, this region can be made to have restricted contribution in the final feature vector. This technique takes advantage of the face regions that are not affected by local variations, such as illumination, facial expression and head pose [60, 61].

2.10.3 Linear Binary Pattern (LBP)

LBP was initially introduced for texture analysis. In LBP a neighbourhood around the centre pixels is selected and each neighbour is compared with the centre pixel and a binary representation is obtained [62, 63, 64]. This represents the local binary pattern for the centre pixel considered and similarly, the LBP is estimated for the entire regions and histogram representation is obtained for all the sub regions [65, 66]. Similarly, Histogram representation of all the sub-regions of the face image is constructed by concatenating the histograms of all the sub regions which represent the gray level structure of the given face image [67]. LBP yields 62.2 % of recognition accuracy on Yale B Extended Face Database.

Enhanced LBP histogram (eLBPH) is an enhancement of LBP. eLBP is used for face recognition [67, 68]. In this methodology, the face image is first divided into small regions and LBP histograms are derived for each region and finally, all the histograms of different sub regions are concatenated to form a global histogram to represent the given face
image[69, 70]. Then histogram matching is performed between the query image and the images stored in the database for recognition.

2.10.4 Local Ensemble Classifier and Hierarchical Ensemble Classifier

Local and Global features are essential for face recognition [71, 72]. The right combination of local and global features facilitates good face recognition accuracy. Global features provide the face recognition system with holistic information about the facial structure, organs, and the facial contours [73, 74]. Local features encode detailed variations in local facial regions [73, 74]. Global features are extracted using 2-D discrete Fourier transformation. Gabor wavelet transformation is used for extracting local features [74]. After feature extraction, classifiers are designed for recognition. A hierarchical classifier is designed using both the global and local feature, whereas Local ensemble classifier is designed using local features. Ensemble learning is a part of machine learning, which is a combination of many local classifiers named as Local Ensemble Classifier [74]. Hierarchical Ensemble Learning improves the recognition accuracy. Hierarchical ensemble Classifier consists of two layers, where the first layer composes of Local component classifiers and other layer consists of local and global components classifier [75]. LEC yields 76.0 % of efficiency on Yale B Extended Face Database.

2.11 SUMMARY

Recognizing illumination affected images still remains a greater challenge for face recognition system. In the literature survey, various categories of illumination pre-processing techniques have been studied and analysed. The literature survey has shed light on key findings that gray level transformation techniques and reflectance field estimation techniques preserve more facial features compared with gradient edge detection technique. Most of the methods under Reflectance field estimation technique require more than one image of an individual acquired at different illumination conditions for constructing a model face, which is used for pre-processing illumination-affected image of an individual. Hence, Gray level transformation
technique is taken for detailed analysis. Histogram Equalization, Gamma Correction and Logarithmic Transformation techniques fall under the category of Gray Level Transformation techniques. Histogram Equalization is simple and efficient Gray Level Transformation technique which is effective for any type of illumination affected image. This research work has modified Histogram Equalization technique to adapt to local regions of the face image and also to improve the overall contrast of the illumination pre-processed image. Adaptation to local regions of the image removes shadows in the image and contrast improvement help achieve clarity in facial features which are essential for face recognition.