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Research Paper

Face Pattern Recognition Under Different Illumination Condition

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ABSTRACT
Research on facial recognition in an unrestricted state has been concentrated on the three traditional cause of variation: Pose, Illumination and Expression (PIE). The lighting of the photographs of people's faces varies; illumination fluctuations present a barrier for facial recognition algorithms. A rising variety of illumination pre-treatment strategies have been the traditional method to solve the problem of face identification under varying lighting situations. The question of how to lessen the impact of varying lighting on acquired photographs remains unanswered, despite the fact that they have achieved fantastic results using a technique of reducing the variances brought on lighting for a successful face recognition system. In this study, the efficacy of illumination normalization strategies was evaluated to lessen the impact of the light on the face images. Homomorphic Filtering for Illumination Normalization, Histogram Oriented Gradient along with Local Binary Pattern to extract facial features, and Feed-Forward Artificial Neural Network (Feed-Forward (ANN)) for classification was employed. Utilizing the YALE B databases, experiments were conducted. The presence of light changes (illumination) of the facial images is lessened using the homomorphic filtering strategy, which enables the suggested framework to offer a high identification accuracy rate of 98.3% and 97%.

KEYWORDS
Face Recognition, Feed-Forward ANN, Homomorphic filtering, Histogram Oriented Gradient, Local Binary Pattern.

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I. INTRODUCTION

Face identification, facial expression detection and other aspects of computer vision has been a hot topic in modern society. The face is very important, as it offers knowledge about how people behave. Face recognition is a biometric procedure for confirming, validating, and identifying people [1]. Comparing a known face to an unknown face is the fundamental purpose of face recognition. This is accomplished by comparing the structure, shape and placement of the eyes, mouth, nose and other facial features of an unknown image to those previously stored in the database. Identification and verification are both possible with facial recognition.

Galton [2] was the first to suggest a formal method for identifying faces. He recommended collecting facial profiles as bends, figuring out their standard and then classifies the profiles according to how much they deviated from the standard. The multi-modular nature of this approach results in a vector of free measurements that may be contrasted and distinguished from other vectors in a face database. It is crucial to grant everyone with secure access as the rate of misbehaviour rises. The method that permits security access is face recognition. Face recognition is a method of identifying or verifying a person from a digital image or a video frame from a video source Thorat et al. [3].

The identification and authentication of people are topics covered by biometrics. There are numerous different biometrics methods, including hand geometry recognition and fingerprint recognition. As the photograph can be taken without the subject's awareness, face recognition is a better biometric technology than other features Abhilasha et al. [4]. A long-standing issue in computer vision is face recognition, because of accessibility of low-cost digital cameras and computers as well as its use in biometrics and surveillance has recently attracted a lot of interest, and has improved recognition performance over the past few decades

Ghorbani, et al. [5]. Therefore, face recognition has a wide application which is usually found in smart cards, security purposes, surveillance, and general identity identification. Furthermore, it can also be used in border restrictions and intelligent biometric identification. Many providers employ advanced technologies in contrast to previous approaches. This research work developed a novel method for face identification that uses both texture and shape to represent the facial image.

This paper is structured as follows: Section 2 presents the related literature. Sections 3 explain different methods used to improve object recognition. Section 4 provides a comparative analysis of this research. Section 5 provides experimental results, and Section 6 presents conclusions and recommendation.

II. LITERATURE REVIEW

Many approaches for face recognition have been proposed, each with a different degree of sensitivity to changes in lighting. Due to significant advancements over the previous decades, and their high robustness, face recognition techniques based on image feature descriptors such as the Local Binary Pattern (LBP) developed by He and Wang [6] are frequently utilized. Each local 3-by-3 neighbourhood structure is converted to a binary series using LBP by threshold holding the neighbouring pixel intensity with the central one. The goal of photometric-based methods, which are based on the retinex theory, is to estimate the illumination component and minimize it by using simple image processing techniques Nefian et al. [7]. LBP functions were used as input in the unrestricted range and showed improvement when combined with conventional techniques Huang et al. [8].

Patel et al. [9] used dictionary-based approaches to look for a description that encompassed the majority or all of the test subject's discriminatory information about the training set. Finding a training set that accurately depicts each and every one of the conceivable illumination circumstances is one of the techniques limitations. The un-lighting method was different class of technique that aims to get rid of illumination-related variance. These techniques can be used in the feature extraction step, where they are referred to as feature-based, or they can be used as a pre-processing step called photometric-based Patel et al. [9]. Relatedly, face recognition, face alignment and face verification have all previously been accomplished using deep neural networks Shepley and Andrew [10].

In order to synthesis fresh photos utilizing the given database under various lighting situations, an approach such the one proposed by Almaddah et al. [11] was employed, which reduced the variation in the matching process. In general, re-lighting or non-lighting techniques are employed to compensate the irregularities brought on by changes in lighting in face detection Nolazco et al. [12]. The goal of relighting techniques is to duplicate the facial image in one or more different lighting situations. These methods' primary drawback is that they necessitate prior lighting information knowledge or estimation. The two main categories of relighting approaches are bootstrap-based and dictionary-based algorithms. A subset that is used to reference model lighting conditions is known as "bootstrap" subset. Muttu and Virani [13] argued in favour of the modified LBP approach. In order to extract facial features, LBP was used and neural networks were utilized for classification. In their proposal, Happy and Routray [13] merged shape and appearance features. LBP was used as an aesthetic feature, and they used the pyramid of histogram of gradients as a shape descriptor. The entire face was not processed, only the active portions. The computational cost was therefore decreased. For dimensionality reduction, they employed linear discriminant analysis and for classification they used SVM with 94.63 per cent accuracy rate and 83.86 per cent identification rate on the CK+ and JAFFE databases, respectively.

The three sources of variation; Pose, Illumination and Expression (PIE) have recently received a great deal of attention in the field of face recognition in unrestricted settings Günther et al. [15]. Fifty two (52) facial key points were identified by Ghadekar et al. [16], who subsequently represented these 52 facial critical points as points and lines. They employed SVM classifier with multicast Adaboost to identify face expressions.

An accurate method to estimate a person's age range based on their facial images was proposed by Khalifa & Sengul [17]. To start, they standardize the size of all photos. All facial pictures from the FG-NET and UTD aging databases had their lighting effects minimized using the histogram equalization approach. Second, the characteristics of these images are extracted using the Histogram Oriented Gradient (HOG) and LBP, and the HOG and LBP features are then merged to get a better prediction. Finally, Support Vector Machine (SVM) and the k-Nearest Neighbor (k-NN) were used for improved classification. To obtain two distinct types of characteristics, Santosh and Sharma [18] used two feature extraction techniques. It is HOG and LBP, with HOG solely depending on the localized region, both approaches are effective at recognizing texture features on the face.

The Flavia leaf dataset was used to evaluate the system's effectiveness after Mohammad et al. [19] published a method of classifying plant leaf photos. HOG and LBP were utilized to extract feature vectors, and a Multiclass Support Vector Machine (SVM) was used to classify the leaf pictures. The accuracy rate for the LBP+SVM approach was 40.6 per cent, and the accuracy rate for the HOG and LBP-based feature combination with SVM was 91.25 per cent. The outcome demonstrates that the HOG+LBP with SVM technique is more effective than both HOG+SVM and LBP+SVM. Recently, Usman et al. [20] proposed a method by examining the effectiveness of illumination normalization techniques by reducing the variations caused by makeup in a face recognition system and applying photometric illumination normalization techniques with their parameters adjusted for face recognition, which amply demonstrates that lighting normalization method improve face recognition outcomes.

III. METHODOLOGY

Three facial recognition models based on features extractor algorithms are used in this research. The models employ LBP and HOG feature extractors. Given that the HOG has a tough time characterizing an object's shape and has a high rate of false detection, it is merged with the LBP feature and, as a result, were able to create the HOG-LBP feature as inputs for the classifying algorithms. The feature vectors produced by each LBP and HOG are supplied separately to ANNs for classification as depicted in figure 1 below.

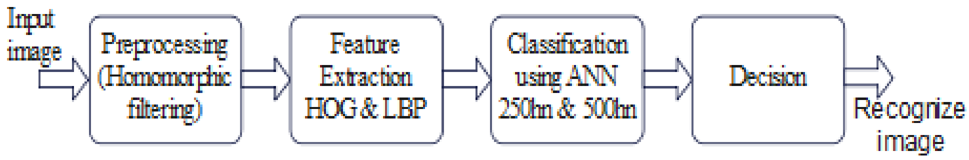

Fig.1: Flowchart summarizing the main stages of the methodology approach

The trials were carried out in a Python programming environment with libraries supplied by Anaconda distributions. The techniques used in this study are relatively generic. The three stages of the suggested approach are listed below.

3.1. Pre-processing Stage

The primary goal of pre-processing is to enhance the image in a way that increases the likelihood that subsequent processes will be successful. To get rid of uneven illumination, Homomorphic filtering, a filtering-based technique was applied. By separating the reflection components, Homomorphic filtering strengthens the high frequency and weakens the low frequency by removing uneven illumination, compressing dynamic range, and enhancing contrast. This technique creates two sub-images from the original image by splitting it vertically into two halves. Each sub-picture is then given the filter, and the resulting sub-images are then added together to create the final image. This technique makes use of a Butterworth high pass filter of first order (n = 1) with a cutoff frequency of $D_0 = 0.25$. The original image was split horizontally after which the same process was used. The output image is created by grouping the two resulting images where $I_{HMH}(x, y)$ is the horizontally divided image and $I_{HMV}(x, y)$ is the vertically divided image following the application of a Homomorphic filter.

$$I_{HMMOD}(x, y) = \frac{1}{2} . [I_{HMV}(x, y) + 0.75 . I_{HM}(x, y)]$$

3.2. Feature Extraction

The challenge of extracting important characteristics from raw data that clearly distinguishes the component images is known as feature extraction. To extract characteristics, there are numerous widely used techniques. In this research, HOG and LBP feature extractors were used in pursuit of high recognition performance.

To apply HOG, a number of significant steps were taken to describe the faces in the photos. First, the input image was divided into blocks, and then each block was further divided into smaller connected cells. It then calculates a histogram of gradient axes for each pixel contained within the cell. Each pixel is modified into angular bins in accordance with these gradient orientations before being participated gradient to its parallel bin. The block histograms, which comprise a one-dimensional array of histograms known as the descriptor, are then normalized.

Utilizing LBP, the input image is divided into non-overlapping blocks of size 16x16 to calculate the LBP characteristics. The 8-bit patterns are then converted into decimals between 0 and 255 by computing LBP patterns at each pixel point inside the blocks. After that, a histogram of each block's LBP patterns is created. In order to limit the size of the histogram, several bins for uniform patterns and a single bin for all non-uniform patterns are produced. An 8-bit LBP pattern known as uniform assumes that a binary pattern comprises no more than two 0-1 or 1-0 transitions.

Finally, join together the histograms from all blocks (in left to right, then top to bottom order) to form a single feature vector. As shown in the below diagram.

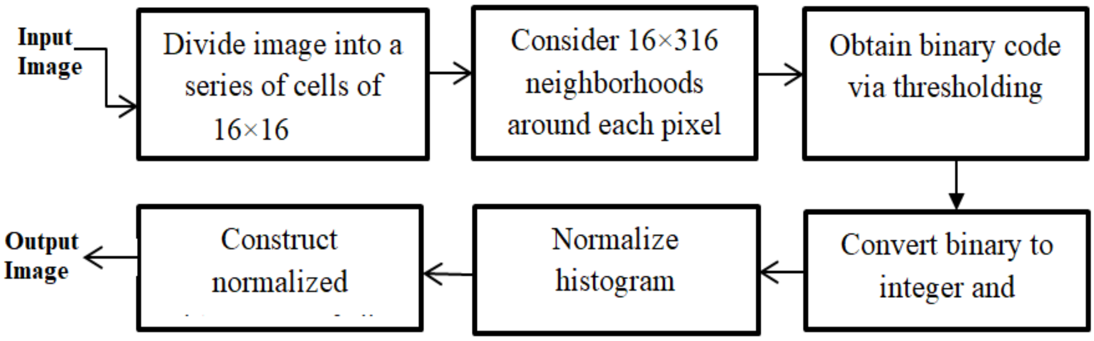

Fig. 2: Flowchart summarizing the main steps of LBP features extractor

3.3. Classification Stage

Any pattern classification task has two basic phases: training and testing. The classifier learns the relationship between samples and their labels from labelled samples during the training phase. The field of pattern recognition and machine learning has seen great success with Artificial Neural Networks (ANN), the input, hidden, and output layers are the three layers that make up most multilayer network models. The input layer is made up of nodes that represent input variables. The outputs of the input nodes are normalized before being sent to the hidden layer, where they undergo further processing using a transfer function. The output variables are contained within the output layer. the basic element of ANN is an artificial neuron, as shown in Fig. 1, which consists of three main components: weights, bias and an activation function. Each neuron receives inputs xi (i = 1, 2, …, n) attached with a weight of wij (j ≥ 1) which shows the connection strength for a particular input for each connection. Every input is then multiplied by the corresponding weight of the neuron connection and summed as:

$$Wi = \sum_{j=1}^{n} w_{ij}\, x_j \qquad (1)$$

Equation (1) adds a bias bi, a form of correction weight with a constant non-zero value, to the summation as follows:

$$Ui = Wi + bi \qquad (2)$$

In other words, it has to do with how well a neural network model can fit various specific training sets. A bias component in a neural network represents the generalization error of the model.x_{ij} is the weight between the *ith* neuron in the hidden layer and the *jth* neuron in the preceding (input) layer, and $x_j$is the output of the *jth* neuron in the input layer as put precisely in equation (1). The summation is transferred using a scalar-to-scalar function known as the "activation or transfer function", $f(Ui)$, to produce a value of the unit's "activation," which is denoted as:

$$y_i = f(U_i)$$

Activation functions enable the nonlinearity that gives neural networks an advantage over linear transformation.

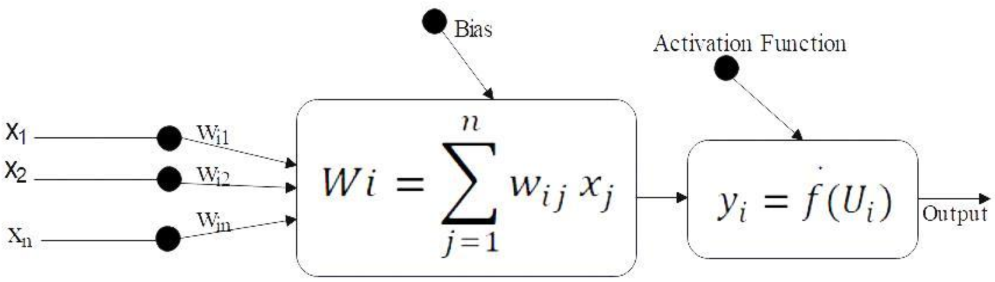

Fig.3 Basic elements of an artificial neural network component

During the training phase, HOG and LBP features are taken from the preprocessed positive and negative samples after applying the averaging method to make them robust, these features are combined to create a single feature descriptor, which is then fed into an ANN to train and test the effectiveness of the face recognition system. A set of 160 test images and 560 training images in.jpg format are included. The test set has 160 positive samples and 22 negative samples, while the training set has 570 positive samples (all involving humans) and 45 negative samples (none involving humans). The training and test images are all 160 X 96 pixels in size.

For each experiment, first, a file is created and saved into the program using the .py extension. The number of neurons, and also the number of iterations are decided beforehand. For each iteration, the feed-forward algorithm is used, and after a specified number of iteration, the error and the accuracy are recorded. The errors were calculated by utilizing the sum of squares of the error method. Below is the number of iterations (or epochs) required to train the perceptron hidden layer sizes of 250 and 500 combined HOG-LBP

Table 1: Number of Iterations (Or Epochs) Required Training the Perceptron Hidden Layer Sizes of 250 And 500 Combined HOG-LBP

Approach	**Number of hidden Neurons**	**Number of epochs**
Combined HOG – LBP	250	56
	500	117

After training, the following rules are used to classify the test images. Perceptron Output Classification: ≥0.6 – face recognized; >0.4 and <0.6 – borderline; ≤0.4 – face not recognized

IV. EXPERIMENT

During the experiment, the output neuron utilizes the sigmoid function, whereas the hidden layer neurons use ReLU activation. The output of the sigmoid function will ensure that the result (output) is between 0 and 1, which can be interpreted as the likelihood of identifying faces in the image. The training's weight update rules are maintained by the two-layer perceptron. With an output label of 1.0 for training images containing faces and 0.0 for training images with no faces were assigned. The experiment was conducted by utilizing a learning rate of 0.1 first. The average error is calculated from the errors of individual training samples after every epoch. The mistake for individual raining sample = Correct output−Network output, with the correct output equals 1.0 for positive samples and 0.0 for negative samples. The training is stopped when the change in average error between consecutive epochs is less than some threshold (e.g., 0.1 or 0.2) or when the epochs is more than (e.g., 1000.)

For the HOG-LBP feature, with the boundaries given above for the LBP included, there are 10×6 squares in the input image and the size of the LBP feature is 10×6×59 = 3,540. The fused HOG-LBP feature, in total, has a size 7524 + 3540 = 11,064. Tables 2, 3, 4 and 5 are summary of the results gotten from the experiments.

The equation below was used to compute the accuracy of the proposed system

$$\text{precision} = \frac{\text{TP} + \text{TN}}{\text{N}} * 100$$

where TP is the number of correctly recognized images while TN are the images that are truly classified as non-recognized images of the network on which the precession predicts the recognition accuracy of the Neural Network and Where N is the total number of the network output after simulation.

Table 2: Result of the Proposed System

Method	**Hidden Neuron**	**No. of Instances Tested**	**Accuracy %**
Combined(HOG&LBP) + Feed-Forward (ANN)	250	20	98.3
	500	20	97

Table 3: Confusion Matrix for the Proposed System for 250 Hidden Neuron

Total No = 182	**Predicted (YES)**	**Predicted (NO)**
Actual (YES)	159(TP)	1(FN)
Actual (NO)	20(TN)	2(FP)

Table 4: Confusion Matrix for the Proposed System for 500 Hidden Neuron

Total No = 182	**Predicted (YES)**	**Predicted (NO)**
Actual (YES)	157(TP)	3(FN)
Actual (NO)	20(TN)	2(FP)

Table 5: Comparison Table of the Existing and Proposed System

Method	**Accuracy**
Adaboost + LNSCT + Neural Network	96.66%
LTV, S&L(LOG-DCT)	62.44% and 68.47%
LBP Method	76.158% and 77.766%
Proposed method ANN(Artificial Neural Network)	98.3% and 97%

4.1 Comparative Analysis

HOG-LBP and multi-layered ANN obtained significantly better recognition results when compared to image-based decomposition methods like LTV, LOG-DCT, and S&L (LOG-DCT), which showed that combining more than one feature extractor can successfully extract the illumination invariant feature when the illumination dominated the main variation. The HOG-LBP approach has the highest recognition accuracy when compared to the other methods. With 98% and 97% recognition accuracy, it is clear that the proposed model extracts more discriminative features and the appropriate information for face recognition in various lighting conditions.

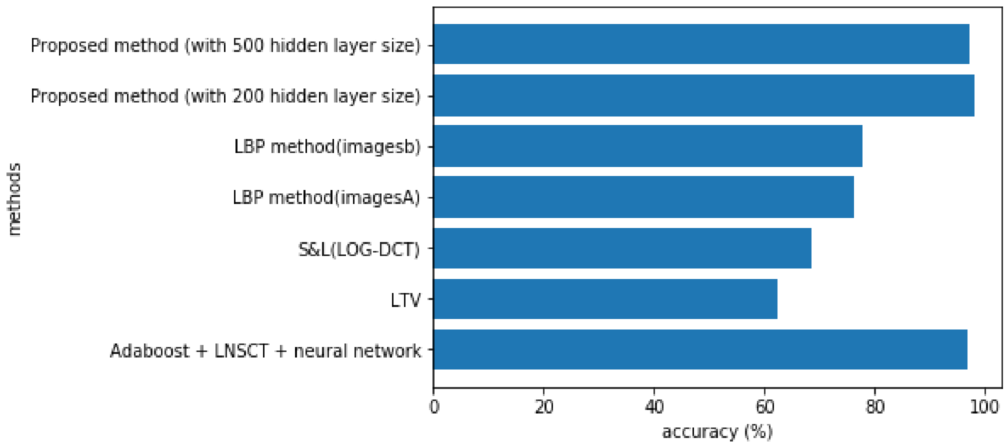

Fig. 5 Recognition accuracy for the different methods

In spite of whether the testing samples' lighting circumstances are good or bad, Figure 5 demonstrates that HOG-LBP and multi-layered ANN perform better than the other methods under comparison while the performance of other methods, particularly LTV and S&L, is unstable (LOG-DCT)

V. RESULTS AND DISCUSSIONS

The "Yale B" dataset was used by the authors for the face recognition algorithm. The model's effectiveness was tested using a total of 635 photos, which were split into training and testing sets consisting of 29% of testing sets and 71% of training sets. For hidden neuron sizes of 250 and 500, the suggested model's overall accuracy was 98.1% and 97%, respectively. The output of the suggested method using hidden neurons with sizes of 250 and 500 is shown in Table 1. Similarly, Tables 2 and 3 display the proposed system's confusion matrix, and Table 4 compare the proposed technique's accuracy with that of the present approach.

Adaboost + LNSCT and LBP + NN classifier are two feature representation-based methods that are resilient in handling face recognition against small illumination variation, but they suffer significantly in poor lighting conditions. For example, the LBP facial recognition method is only 76.158% and 77.766% on images ‘A’ and images ‘B’, respectively. The proposed HOG-LBP and multi-layered ANN methods, however, achieve up to 98.3% and 97% accuracy rates, respectively. The suggested method beat Adaboost + LNSCT and LBP methods in part because of their difficulty classifying photos with low and high contrast, as well as the fact that the speed of recognition declines with feature vector length.

VI. CONCLUSIONS

In this paper, an approach for face recognition on YALE B datasets was presented. Homomorphic filtering was applied to face images in order to remove an uneven light changes. It then combined the LBP and HOG features extracted from part of the faces and finally used ANN for face recognition. The evaluation of the methods was performed on the database consisting 71% as training set and 29% as testing sets. The data used to train the neural network proved to be sufficient enough to reach good recognition rates for both methods. The method based on the local binary pattern and Histogram Oriented Gradient operator achieved good results on both the modified and unmodified subset of the database. Despite the rather simplistic implementation of both the two methods, it is shown that they all perform well and that it could successfully be used for identification, increased robustness and for recognition accuracy. And the research also compared the result to some recent studies that focuses on face recognition in different lighting condition.

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