

**DEEP LEARNING FOR FACE RECOGNITION BASED ON LOG-GABOR AND LBP**

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Abstract - The major goal of this work is to detect or find faces under difficult lighting circumstances. Face recognition technology is something we constantly depend on. However, lighting is a major problem with face recognition, making it harder to detect faces. In this article, we gave an excellent solution to this issue. To begin, illumination preprocessing is employed to mitigate the unfavourable impact of abrupt changes in lighting on face pictures. Second, the Log-Gabor filter is used to extract the LBP (Local Binary Pattern) features of the photos subblock in order to create Log-Gabor feature images of varied sizes and orientations. Texture feature histograms are constructed and fed into the deep belief network (DBN) visual layer.

Keywords—complex illumination; Log-Gabor filter; LBP features; deep learning

I. INTRODUCTION

Face recognition technology of this sort is used in sensitive areas such as airports to allow allowed personnel, such as crew members, to pass through numerous security levels without having to provide identification. For safe online transactions, face verification may be used instead of PIN numbers and passwords. PIN numbers and passwords are difficult to remember. Despite being quite effective for authentication, they are readily stolen. Face recognition technology may be used in public or secure environments for identification and surveillance to detect illegal conduct. Face recognition may be used in government security concerns such as national ID cards, passports, and licences, among others. In today's environment of increasing importance for security and organisation, identification and authentication techniques have become a vital technology in a number of fields: building entrance restrictions; access control for everyday activities such as withdrawing money from a bank account or dealing with the post office, for computers in general or for automated teller machines in particular, or in the well-known field of criminal investigation. The necessity for reliable personal identity has fueled interest in biometrics in computerised access control. Biometric identification is the method of automatically identifying or verifying a person based on a physical feature or personal trait. The term "automatically" refers to the necessity of a biometric identification system to swiftly detect or confirm a human feature or attribute with little to no user input. Biometric technology was developed for use in high-level security systems and the law enforcement industry. Behavioural biometrics include movements like as typing and distinctive rhythms. Physical biometric systems use people's eyes, fingers, hands, voices, and faces to identify them. People have used physical characteristics such as the face, voice, and movement to identify one another for thousands of years. The uniqueness of human fingerprints has led to a significant and beneficial discovery of person identification. Following this finding, several major law enforcement organisations embraced the idea of first booking offenders' fingerprints and storing them in a database (card file).

II. EXAMINE TECHNICAL SPECIFICATIONS

A. Log-Gabor filter electing:

The local frequency responses can be used by the Log-Gabor filter to describe a signal. This basic signal analysis method has numerous uses in the field of signal processing. The Log-Gabor filter might be advantageous for any application that uses Gabor filters or other wavelet basis functions. Nevertheless, depending on the specifics of the design issue, there could not be any gain. However, because it has been demonstrated to better capture the statistics of natural images, the Log-Gabor filter has been found to be particularly helpful in image processing applications. Field developed the Log-Gabor function as a substitute for the Gabor function.

$$G(f) = \exp \left\{ \frac{\left(-\log \frac{f}{f_0} \right)^2}{2 \left(-\log \frac{k}{f_0} \right)^2} \right\}$$

where k is the control bandwidth and f_0 is the zeroth frequency of the filter. The Log-Gabor filter has two distinguishing features. To begin with, since log-Gabor functions never include a DC component by design, the influence of lighting on image processing is quite modest, which helps to reduce the detrimental impacts of illumination on face recognition. Second, the high frequency end of the log Gabor function transfer function has an extended tail. Log-Gabor functions should be able to encode real pictures more successfully than standard Gabor functions, which would overrepresent the low frequency components and underrepresent the high frequency components in any encoding.

B. LBP operator:

A Local Binary Pattern (LBP) identifies pixels in an image by thresholding each pixel's neighbours and converting the result to a binary integer. LBP texture operators are becoming more popular in a range of applications because to their discriminative capability and computational simplicity. This method integrates the previously disparate statistical and structural approaches of texture analysis. The LBP operator's robustness to monotonic gray-scale changes produced, for example, by variations in lighting is perhaps its most essential quality in real-world applications. Ahonen et al. (2006) established a fundamental framework for LBP-based face description that is computationally simple and enables for real-time picture analysis. By separating the face picture into local areas, LBP texture descriptors are recovered individually from each region. As illustrated in Fig. 1, the descriptors are then concatenated to give a global description of the face given below.

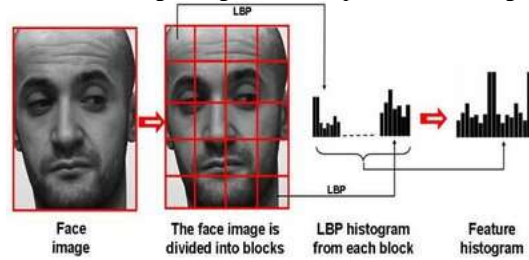


Fig. 1. Basic LBP operator.

The face is characterised at three levels of locality in this histogram: the LBP labels identify the patterns at the pixel level, they are averaged across a small area to offer information at the regional level, and the regional histograms are merged to generate a global description.

where $s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$ g_c

is the centre pixel of a window with dimensions $m \times n$, and $g(P=0, 1, 2, \dots, P-1)$ represents the equally dispersed pixels with the number P on the circle.

$$LBP_{g_c} = \sum_{i=0}^{P-1} s(g_i - g_c) 2^i$$

The LBP operator is applied to each pixel of the picture in the aforementioned computation procedure to produce the matching LBP value to describe the texture information of the image.

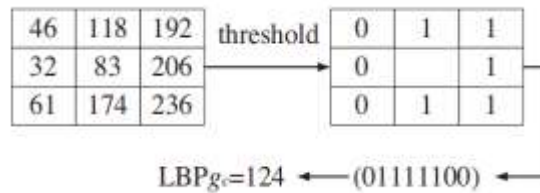


Fig 2. LBP Values

c. Deep Belief Network (DBN):

A deep belief network (DBN) is a sort of deep learning that tackles issues that regular neural networks do not. They do this via the network's layers of stochastic latent variables. Because these binary latent variables, feature detectors, and hidden entities are binary variables, they may take any value within a specified range with a particular probability. The DBN's top two layers are directionless, with the top layer directly coupled to the bottom layer. DBNs are distinct from standard neural networks in that they may function as both generating and discriminative models. Traditional neural networks, for example, can only be taught to categorise pictures. DBNs are also distinct from other deep learning algorithms such as restricted Boltzmann machines (RBMs) and autoencoders in that they do not handle raw inputs, as RBMs do. Instead, he uses an input layer with one neuron for each input vector and proceeds through several levels until he reaches the final layer, where the output is formed using the probabilities obtained from the preceding layers.

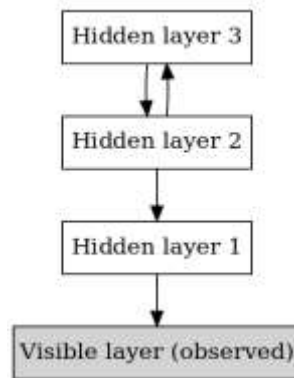


Fig 3. Deep Belief Network

Some common deep architectures have been developed, the DBN consists of a number of unsupervised Restricted Boltzmann Machines (RBM). The joint distribution between visible units and hidden units for a DBN with L-layer hidden units may be described as.

$$p(v, h^{(1)}, h^{(2)}, \dots, h^{(l)}) = P(v|h^{(1)})p(h^{(1)}|h^{(2)}) \dots P(h^{(l-1)}|h^{(l)})$$

where $v=h(0)$, v is the DBN visible unit, and $h(k)$ ($k=1,2,\dots,l$) is the k layer hidden unit.

III. IMPLEMENTATION

MODULES

Face Recognition

Face recognition is done by following modules,

1. Image Acquisition
2. Preprocessing
3. Face Detection
4. Feature Extraction
5. Recognition

DESCRIPTION OF THE MODULE:

1. **Image Acquisition:** Images for testing and training are being collected from the Yale B+ database.

2. **Preprocessing:** When dealing with Complex Illumination Conditions, preprocessing is a vital step. We increase the brightness uniformity of the picture by using a weighted least square filter, illumination modification (gamma correction), and an adaptive histogram equalisation (AHE) approach for contrast enhancement. As a result, we increased the image's brightness uniformity.

3. **Face Detection:** Face detection is the third step of face recognition. To identify the face in a test picture, a computer vision face detection

technique is utilised. Following that, the identified face was cropped for the following procedure.

4. **Feature Extraction:** Following the identification of faces, we investigated the log gabor filter and the local binary pattern for feature extraction. Log-Gabor filtering is performed to the modified and identified face picture to get local feature images of various scales and directions. The recovered local feature image from log gabor is then separated into subblocks, and the image is partitioned into 4 4 blocks. Each subblock's LBP texture characteristics are extracted. The LBP texture feature is formed by connecting the features of each subblock.

5. **Face Recognition:** This is the last level of face recognition. Deep learning, i.e. Face recognition is accomplished using DBN. DBN network learns the above texture properties to accomplish the classification or recognition.

.PRESCRIBEDMETHOD

The suggested approach in this study is shown in the flowchart below.

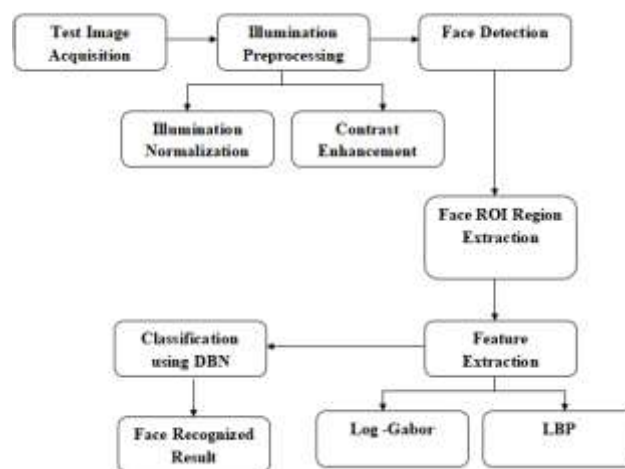


Fig 4. Suggested Approach

As indicated in the picture above, Log-Gabor, LBP, and DBN are employed in this article to examine face recognition under difficult lighting situations. The suggested algorithm's stages are as follows.

(1) We first increase the brightness uniformity of the picture before employing the Log-Gabor filter to preprocess it. The adaptation factors are initially estimated for each pixel in the retinal local adaptation model by conducting a low-pass filter on the input picture, as illustrated below.

$$H(p) = I_c(p) * G_f$$

$$G_H(x, y) = e^{-((x^2 + y^2) / 2\sigma_f^2)}$$

where p is an image pixel, H(p) is the adaption factor at pixel p, I_c is the intensity of the input picture normalised between [0, 1], represents the convolution operation, GF is a two-dimensional Gaussian filter with spatial constant, and σ_f=3 is used. The following local nonlinearity operation is applied to the input picture I_c.

$$I_{cl}(p) = (I_c(\max) + H(p)) \frac{I_c(p)}{I_c(p) + H(p)}$$

The phrase refers to a normalisation factor that guarantees I_c is scaled in the range [0, 1]. I_{cl} is further normalised to enhance the preprocessed picture with the largest intensity range.

$$I_{clf} = \max_v \frac{I_{cl} - \min I_{cl}}{\max I_{cl} - \min I_{cl}}$$



(2) After preprocessing the input picture, the altered face image is subjected to Log-Gabor filtering to yield local feature images of varying sizes and orientations.

(3) In this study, the database of face pictures is separated into training and testing sets; each image in the training and testing sets is partitioned into subblocks, and the partition of each image is 4 4. Each subblock's LBP texture characteristics are extracted. The feature of each subblock is joined to generate the sample's LBP texture feature, which is designated H.

(4) The texture feature vector (H) obtained in step three is loaded into the DBN visible layer. The combined distribution of DBN visible and hidden units is seen in below.

$$\begin{aligned}
& p(H, h^{(1)}, h^{(2)}, \dots, h^{(l)}) \\
& = P(H|h^{(1)})p(h^{(1)}|h^{(2)})\dots P(h^{(l-1)}|h^{(l)})
\end{aligned}$$

In the above equation, h(1), h(2),... Higher level characteristics such as, h(l) are learnt layer by layer. In the paper, the number of hidden layers is set to 2, while the number of hidden units is set to 200. It is possible to acquire the combined distribution of the visible layer and two hidden layers via

$$p(H, h^{(1)}, h^{(2)})=P(H|h^{(1)})p(h^{(1)}|h^{(2)})$$

H denotes the visual layer. The first hidden layer is h(1), and the second hidden layer is h(2). The first hidden layer's active probability of hidden units is determined by

$$P(H_i=1|h)=\sigma(b_i + \sum_{j=1}^{num} W_{ij} H_j)$$

where H_i represents the visual unit and num represents the number of visual units.

(5) The DBN iterative approach is described to optimise the weights W_{ij} for the ideal training network; the iteration number is m. The ideal network is determined by the training set's maximum probability function value being the greatest. The greatest probability function is obtained by

$$P = \arg \max_w E \left[\sum_{h \in H} \log p(h) \right]$$

w is the weight matrix, while H is the LBP texture feature matrix of the training set. The number of iterations (m) is set at 3000. The learning rate is adjusted to 0.001 according to the modification. The ideal network is achieved after step (5). The testing samples' category labels are produced by a classifier at the top of the DBN network.

DESIGN OF CONTROLS

The input design connects the information system with the user. It comprises developing requirements and methods for data preparation, which are required to turn transaction data into a processable format. This may be accomplished by having users enter data directly into the system or by having the computer read data from a written or printed document. The input process is developed with the goal of decreasing the amount of input required, avoiding mistakes, minimising delays, minimising unnecessary phases, and keeping a simple workflow. The input is designed to provide security, usability, and privacy protection. Input Design considered the following factors:

1. What data should be supplied as input?
2. How should the information be arranged or coded?
3. The discussion to direct the contribution of the operations personnel.

4. Procedures for generating input validations and what to do if an error occurs.

OBJECTIVES

1. Input design is the process of converting a user-centered input description into a computer-based solution. The goal of this design is to avoid errors during the data entering process and to offer clear instructions to management on how to retrieve reliable information from the computerised system.

2. It is achieved by creating user-friendly displays capable of handling huge quantities of data entering. The goal of input design is to make data entry easier and error-free. Because of the thorough design of the data input page, any data manipulations are feasible. It also includes tools for viewing records.

3. When data is input, it is validated. Data may be input by using screens. Appropriate communications are given when required so that the user is not stuck in a labyrinth of instant messages. The purpose of input design is to provide an easy-to-understand input arrangement.

PRODUCT DEVELOPMENT

A high-quality output is one that clearly displays the information and meets the demands of the end user. The outputs of any system are how processing results are communicated to users and other systems. During output design, it is determined how information will be displaced for both immediate demand and hard copy output. It is the most important and direct source of information for the user. The efficient and intelligent output design improves the interaction between the system and the user decision-making.

1. The process of developing computer output should be well-organized and well-thought out; suitable output must be developed while ensuring that each output portion is structured in such a way that users will find the system easy to use. It is critical to locate the exact output that will fulfil the standards when assessing computer-generated output for design purposes.

2. Choose information display methods.

3. Create papers, reports, or other formats containing system-generated data.

The output form of an information system should fulfil one or more of the following objectives.

1. Provide information on previous activity, present status, or future estimates of the Future.

2. Indicate significant events, opportunities, issues, or cautions.

3. Initiate an action.

4. Confirm a motion.

IV. RESULTS AND OUTCOMES

The accurate results of the project that had mentioned in the paper are distributed below. As our project deals with many processes that given below in step wise manner. Steps of the face detection under illumination conditions are given below:

Step 1:



Fig 5. Input Image Capture

As in step-1 the image with face is taken as input and the first step of the project is applied to the image. The second image in the above figure shows the illuminated preprocessed image.

Step 2:

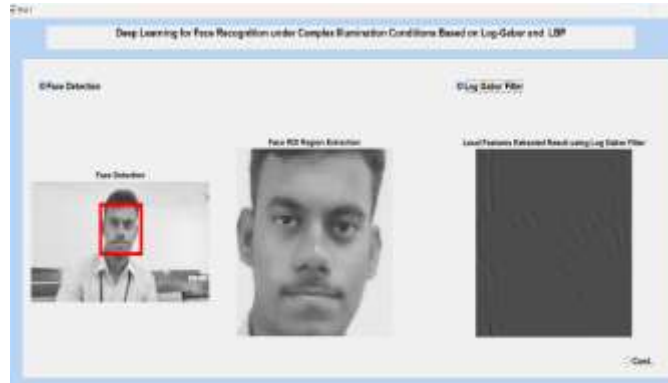


Fig 6. Illuminated Pre-processed Image

In step-2 the illuminated preprocessed image is taken as input to detect the face and as well as the log gabor filter is applied to the image.

Step 3:

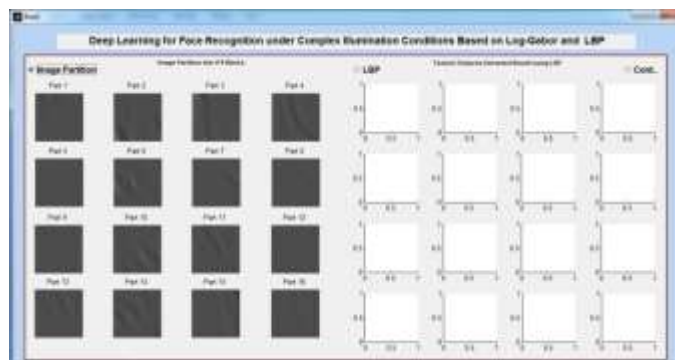


Fig 7. Partitioned Image

The step-2 output image is taken, and the image is partitioned to apply the LBP filter

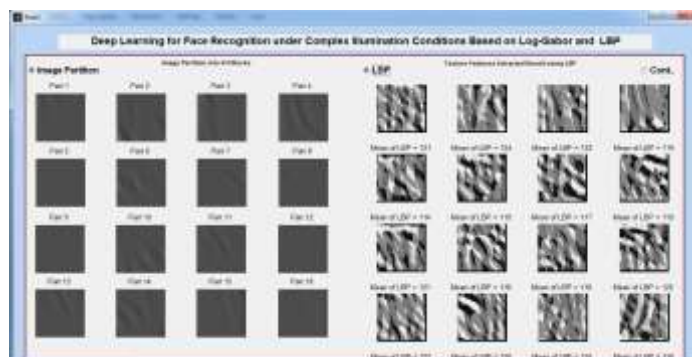


Fig 8. LBP Filter Applied Resultant Output

The LBP filter is applied and the resultant output image is shown in the above figure.

Step 4:



Fig 9. DBN Algoritm Applied

As this is the last step of the output, it uses the DBN algorithm to recognize the face. If the face is detected then it returns 1 or else it will return 0. In the predicted class output.



Fig 10. Performance Analysis

As the last step it will give an perfect performance analysis in terms of accuracy, precision, etc.

V. FINAL REMARKS

This research proposes a unique deep learning-based strategy for dealing with the negative effect of illumination variation in face recognition. Illumination preprocessing is used to mitigate the negative impact of severe lighting fluctuations on facial photographs. The Log-Gabor filter is used to produce Log-Gabor feature pictures of various scales and orientations, and image LBP features are extracted. These textural characteristics are then learnt by to finish the categorization and recognition, use the DBN network. When compared to several state-of-the-art methods, experimental findings reveal that the suggested technique outperforms them in facial recognition.

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