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GENDER IDENTIFICATION USING TEXTURE AND EDGE FEATURES FROM FACIAL IMAGES

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***Abstract*-This paper mainly focuses on gender identification with various front facial images. LBP, DRLBP, HOG are powerful techniques could be effectively exploited for this purpose. A set of HOG parameters can make this descriptor one of the most suitable to characterize facial peculiarities by edge analysis whereas LBP and DRLBP parameters are used for texture analysis. After face detection, feature extraction is being performed by combining LBP with HOG and also DRLBP with HOG separately and results are characterized by their performance percentages. Training is done using facial dataset consisting of front face images. Support vector machine classifier is used for separation of two classes by choosing best hyper plane. So that when test image is given support vector machine classifies the gender successfully. We obtain performance of 97% by applying support vector machine (SVM) with the DRLBP and HOG and 95% by applying SVM with LBP and HOG.**

Key Words —Local Binary Pattern, Dominant Rotated Local Binary Pattern, Histogram of oriented gradients, Support Vector Machine.

1. INTRODUCTION

Gender classification is a fundamental and easy task for human beings, as many social functions critically depend on the correct gender perception. Human faces provide important visual information for gender perception. The facial information is one by which human can make difference between men and women, although there exists a wide range of possible facial images. However, in real-world applications, gender classification needs to be performed on real-life face images captured in unconstrained scenarios. Gender recognition in real-time faces is much more challenging compared to the case for faces captured in constrained environments. In many real applications (e.g. human–computer interaction and visual surveillance) input data generally consists of face along with upper region[8]. There are many features in face from which we can identify the gender. In our Proposed approach, we take texture and edge as a key features[3]. First face is detected from the image using Viola Jones face detection algorithm. Facial images alone can be used to classify the images of teenagers using edge analysis, but skin tone varies for people of different age groups. To avoid the effect of aging in classification, texture analysis is taken into account to classify people of all age groups. Then features are extracted from detected faces using various algorithms like LBP, DRLBP, HOG, etc., used for

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texture and edge analysis respectively. LBP is the most popular texture classification feature. It is robust to illumination and contrast variations as it only considers the signs of pixel difference. Histogramming LBP codes make the descriptor resistant to translations within the histogramming neighbourhood[2]. However, it is sensitive to noise and small fluctuations of pixel values. To handle this, Dominant Rotated Local Binary Pattern has been proposed[1]. In comparison to LBP, rotation invariance is achieved by computing the descriptor with respect to a reference in a local neighbourhood. The proposed approach not only retains the complete structural information extracted by LBP, but it also captures the complimentary information by utilizing the magnitude information, thereby achieving more discriminative power[6]. Like LBP it has also been used for texture classification and face detection. In this paper we combined the operation of LBP with HOG and DRLBP with HOG separately to improve the accuracy. Histogram of oriented gradients (HOG) is a feature descriptor used to detect objects in computer vision and image processing. The HOG descriptor technique counts occurrences of gradient orientation in localized portions of an image - detection window, or region of interest (ROI) . Different objects have different shapes and textures. It is therefore desirable to represent objects using both texture and edge information. From the features extracted classification is done by using some classifiers like SVM, KNN, decision tree, multiclass SVM etc[5]. The classifiers are typically trained using large sets of labelled training examples. So that it can easily classify the data points when testing examples are provided. The overall performance critically depends on three elements feature set, classifier, training set.

2. METHODOLOGY

The working of gender identification algorithm includes the following steps

1. Gray Scale and Resize
2. Face detection
3. Feature extraction
4. Gender Identification

The first step involves face detection which is done through Viola Jones algorithm and feature extraction by exploiting LBP, DRLBP, and HOG. And gender is classified using support vector machine algorithm.

To recognize genders from videos, a face detector is applied on each images at first.The breakthrough in face detection happened with Viola & Jones algorithm. Using a cascade of “weak-classifiers”, using simple Haar features, can after excessive training yield impressive results. Viola Jones Algorithm used for face detection.Using trained data Viola Jones algorithm classifies as face or non face. Four working ingredients are Haar features used to detect presence of the features in given image, the integral images for feature computation, Adaboost for feature selection, attentional cascade for efficient computational resource allocation.

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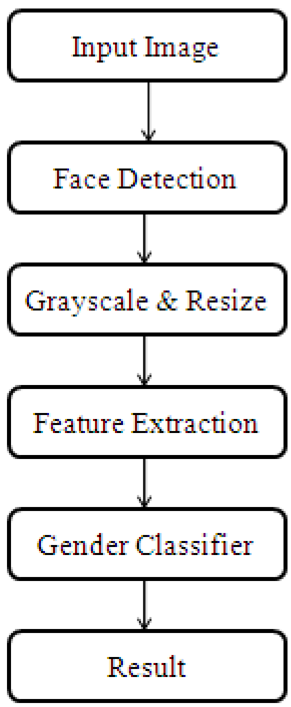

Fig.2.1. Architecture of Gender Classifier

LBP is a simple and efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number[7]. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It divide face images into 3*3 pixels block. Select one pixel as center if center pixel value is greater than neighbor write '1' otherwise write '0'[8].Another extension to the original operator is the definition of so-called uniform patterns, which can be used to reduce the length of the feature vector and implement a simple rotation-invariant descriptor. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is traversed circularly[1][12]. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010010 (6 transitions) are not. In the computation of the LBP labels, uniform patterns are used so that there is a separate label for each uniform pattern and all the non-uniform patterns are labeled with a single label.

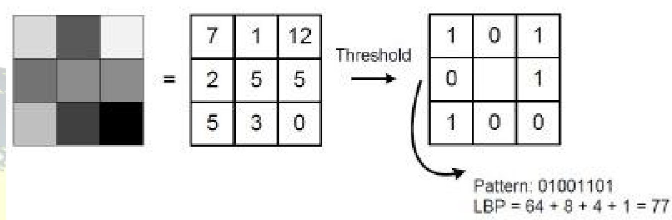

Fig.2.2 The stages of LBP feature computation and thresholded w.r.t. to the value of the central pixel to produce a binary code.

DRLBP is extension of local binary patterns (LBP). As we know LBP can achieve effective description ability with appearance invariance and adaptability of patch matching based methods. However, LBP only thresholds the differential values between neighbourhood pixels and the focused one to 0 or 1, which is very sensitive to noise existing in the processed image[12]. This study extends LBP to Dominant Rotated Local Binary Patterns (DRLBP). The problem of variations to rotations in LBP arises due to the fixed arrangement of weights. As the weights are aligned in a circular manner, the effect of image rotations can be countered by rotating the weights by the same angle while computing the descriptor. Since the angle of the rotation cannot be known, we propose an adaptive arrangement of weights based on the locally computed reference direction[13]. The reference direction should be such that if an image undergoes a rotation, it should also undergo

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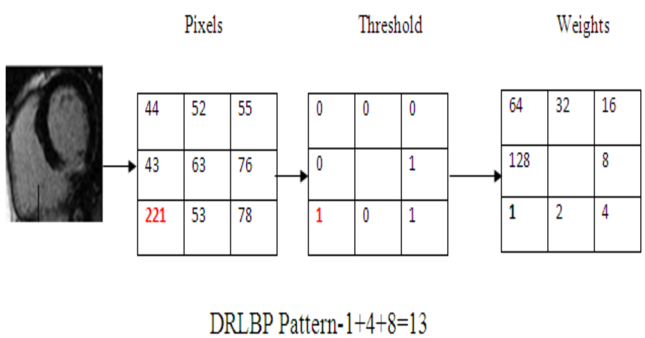
a rotation by the same angle. In our experiments, we have tested different choices of the reference direction, such as the gradient, weighted difference between the pixels, etc. The best results were obtained with what we call, the *Dominant Direction*. The *Dominant Direction* is defined as the index of the neighboring pixel whose difference from the central pixel is maximum[14].



When Rotated,

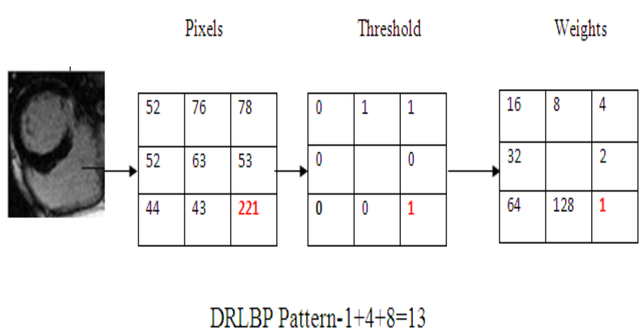


Fig 2.3 The stages of DRLBP feature computation and thresholded w.r.t. to the value of central pixel to produce a binary code.

Histogram of oriented gradients (HOG) is a feature descriptor used to detect objects in computer vision and image processing. The HOG descriptor technique counts occurrences of gradient orientation in localized portions of an image - detection window, or region of interest (ROI)[9]. Implementation of the HOG descriptor algorithm is to divide the image into small connected regions called cells, and for each cell compute a histogram of gradient directions or edge orientations for the pixels within the cell then discretize each cell into angular bins according to the gradient orientation. Each cell's pixel contributes weighted gradient to its corresponding angular bin. Groups of adjacent cells are considered as spatial regions called blocks. The grouping of cells into a block is the basis for grouping and normalization of histograms. Normalized group of histograms represents the block histogram. The set of these block histograms represents the descriptor[10][11]. Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. There are many hyper planes that might classify the data. One reasonable choice as the best hyper plane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyper plane so that the distance from it to the nearest data point on each side is maximized. If such a hyper plane exists, it as the maximum-margin hyper plane and the linear classifier it defines is known as a maximum margin classifier[5]. [4] proposed a system, this system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In the pre-processing stage, Mean shift filter is applied to CT image process and statistical thresholding method is applied for reducing processing area with improving detections rate. In the Second stage, the liver region has been segmented using the algorithm of the proposed method. Next, the tumor region has been segmented

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using Geodesic Graph cut method. Results show that the proposed method is less prone to shortcutting than typical graph cut methods while being less sensitive to seed placement and better at edge localization than geodesic methods. This leads to increased segmentation accuracy and reduced effort on the part of the user. Finally Segmented Liver and Tumor Regions were shown from the abdominal Computed Tomographic image.

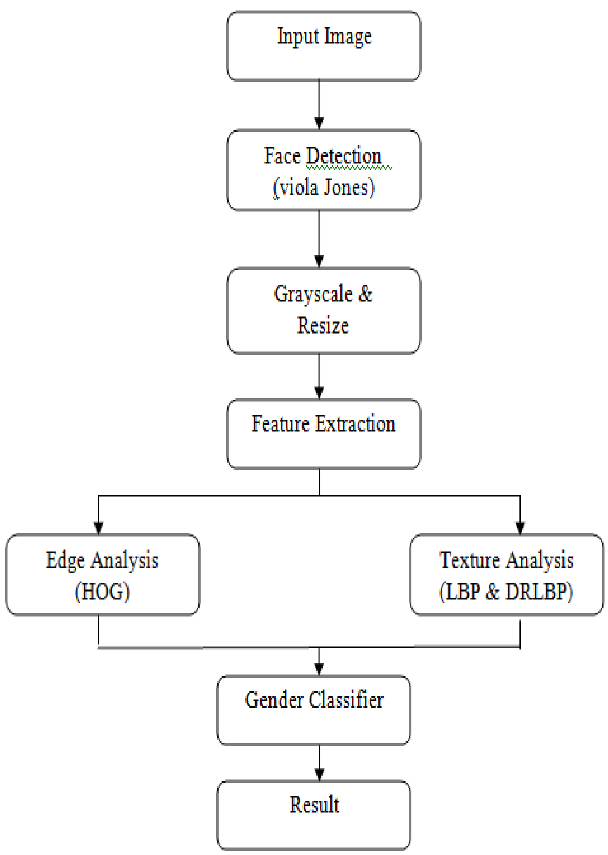

Fig.2.3. Block Diagram for Gender Classification

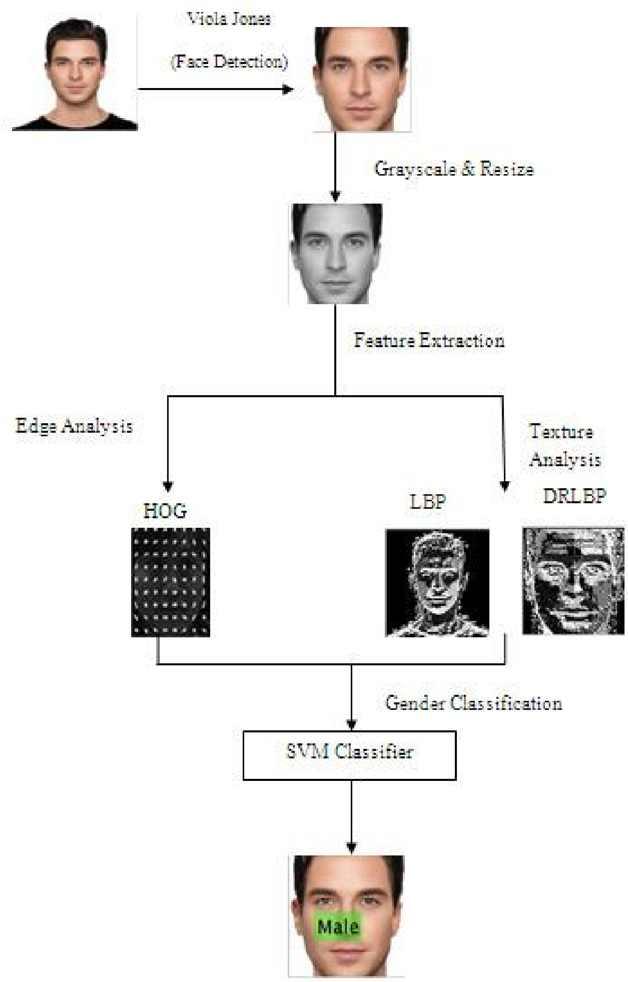

Fig. 2.4. Methodology

3.DATASET USED

From FEI database around 120 images showing different facial expressions has been taken. From that 60 images are used for training exhibiting some expressions like angry, fear, sad, surprise, normal, smile, so that classifier is trained accordingly. Then another 60 images are used for testing showing similar expressions as used in training data. In the database there were some images of males appearing as a females and females appearing as males, this method successfully classified the images into males and females.

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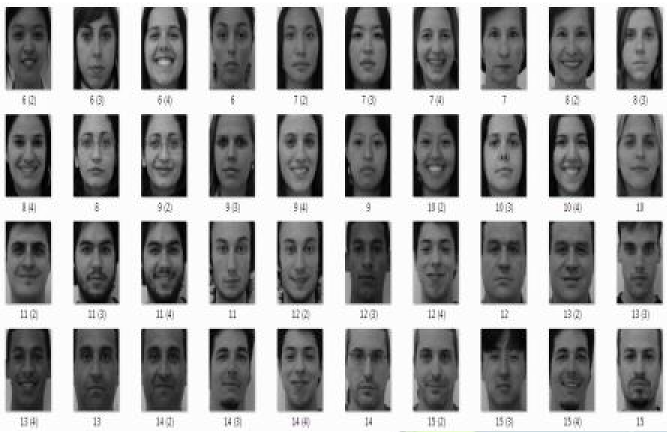
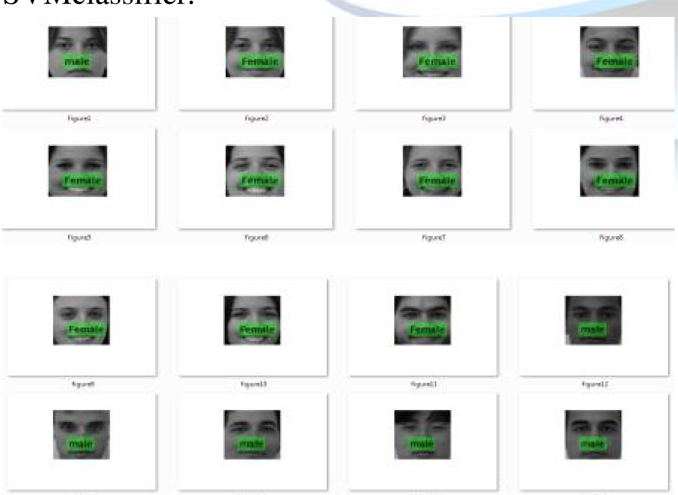


Fig.3.1. Dataset Collection

4.EXPERIMENTAL RESULTS

The system is tested with various input images. An experimental result of the proposed system shows accuracy of 95% while using LBP and HOG. Where LBP is only expression sensitive. And percentage of accuracy is increased upto 97% by employing DRLBP and HOG since it is both edge and texture sensitive. From the features extracted uing above algorithms gender is classified using SVMclassifier.



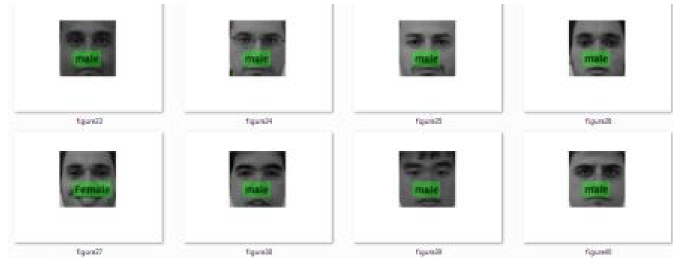


Fig.4.1 Classified images

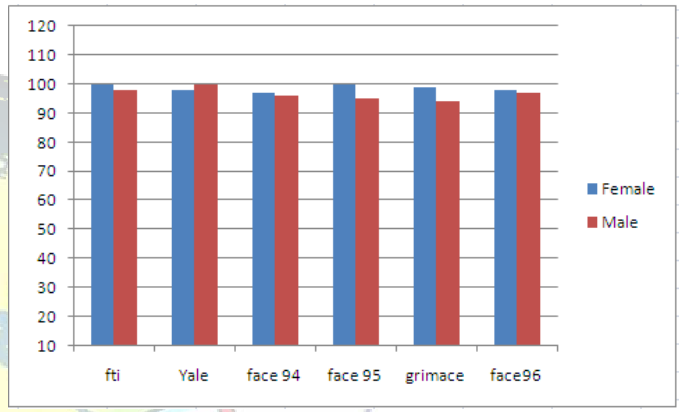


Fig. 4.2 Accuracy of DRLBP and HOG Algorithm

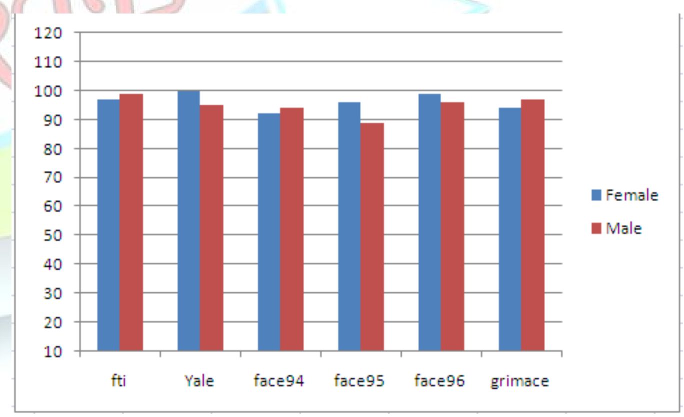


Fig. 4.3 Accuracy of LBP and HOG Algorithm

5.CONCLUSION

In this paper, we classified gender with various facial images. To classify the gender, first to detect the face, once the face is detected, features are extracted. Then we apply SVM classifier for gender classification. The proposed system has a low complexity and reduced computational time and is suitable for real time implementation. This method successfully classified male and female with accuracy of 98% while using DRLBP and HOG with SVM and 95% when LBP and HOG applied to SVM.

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