Medical Image Processing, Human Face Classification, Face Recognition and Medical Imaging: Performance Evolution Histogram of Orientation Gradients

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Abstract

In view of the common conditions and the security of the country from all the blackmail that is urging, whether on the level of the Internet and social communication, there was an urgent need to secure all institutions and also secure our phones and our possessions from laptops and others using more accurate safety methods than these methods I used the method of destination classification, i.e. identifying the destination so that it is possible to secure We can see you through the fingerprint of the destination, and this method that is popular recently. In this paper, HoG algorithm was used and this algorithm is considered one of the powerful ways to extract the features that we need in the classification process relying on one of the methods of learning a machine an algorithm was used naive Bayes. After that, the system is evaluated by calculating the accuracy, specificity, and sensitivity and it is found that the efficiency of the system reaches 98%.

Keywords— *HoG, Naïve bayes, Bilateral Filter, histogram equalization.*

Introduction

Biometry has recently become one of the most widely studied fields of many sub-disciplines, such as machine vision, pattern classification and manipulation of images. Biometry's main objective is to create systems that can identify individuals with certain observable characteristics, such as their face, fingerprints, iris, etc. There does not seem to be any particular way of obtaining and reading biometric data that does the greatest job of ensuring safe authentication(1). Any of the multiple biometric authentication approaches has something to recommend to them. Some are less invasive, others can be performed without the subject 's knowledge and others are really hard to fake. Automatic face classification, along with other biometric methods such as fingerprint verification and speech classification, is a thoroughly studied field of Computer Science. The human face plays a major role in our social contact, conveying the personality of individuals. The detection of people by the distinctive features of their faces is Facial Classification (2). In the past few years, biometric facial classification technology has gained considerable interest due to the potential for a wide range of uses in both enforcement and non-law enforcement, using the human face as a gateway to protection (3). Face classification in images is a difficult task due to their variable look and the vast spectrum of poses they will take. The first need is a comprehensive feature set that allows the human type to be cleanly discriminated against, even under challenging lighting in cluttered surroundings. The analysis of facial detection feature sets reveals that locally normalized Histograms of Oriented Gradients (HOG) descriptors have superior efficiency compared to other current feature sets. HOG is one of the well-known object classification features. HOG features are defined by taking orientation histograms of edge intensity in a local environment (4).

In this paragraph, the range of research that has been used classification of facial using HoG feature extraction will be reviewed as shown below:

The feature-based technique for 2D face images was implemented. For function extraction, accelerated robust features (SURF) and scale-invariant feature transformation (SIFT) are used. For experimental analysis, five public databases, namely Yale2B, Face 94, M2VTS, ORL, and FERET, are used. In this thesis, different combinations of SIFT and SURF features have been evaluated with two classification techniques, namely decision tree and random forest. Writers with a mixture of SIFT (64-components) and SURF (32-components) have recorded a maximum recognition accuracy of 99.7 percent has been presented [5].

Attempts have been made to explain the technical phenomena in which the solution to facial recognition based on the decision tree is suggested using SVM and SURF. Pre-processing, which requires both the input image and all the images processed in the archive, comes first in this technique. Secondly, to remove facial attributes, image processing operations are used. For the purpose of preparation and checking, the last decision tree with SVM and SURF foundation methodology is used. With regard to the error rate, matching time and overall accuracy graph, the suggested method shows better performance. More specific and better results are provided by the use of the decision tree has been presented [6].

By applying two normalization operations to two of the layers, a modified Convolutional Neural Network (CNN) architecture is proposed. Network acceleration was given by the normalization on process, which is batch normalization. To remove distinctive face characteristics, the CNN architecture was used and the Softmax classifier was used to identify faces in the CNN fully linked layer. In the experiment part, Georgia Tech Database showed that the proposed solution has enhanced the face recognition efficiency with better recognition outcomes has been presented [7].

To predict the face, naive Bayes is used to characterize the outcome of eigenface function extraction. To sharpen the precision, the normalization z-score is applied. The 200 datasets are divided into data training and checking by means of cross validation (k=10) to see the efficiency of the proposed system. The findings indicate that the proposed approach can predict up to 70 percent of the face picture. In comparison, the precision of estimation increases to 89.5 percent (on average) by adding Z-Score normalization has been presented [8].

To extract the local binary features of the image, a local binary pattern (LBP) and a center-symmetric local binary pattern (CS-LBP) were applied. For facial recognition, Euclidean distance, histogram intersection, and chi-square distance are used. On the Japanese Female Facial Expression (JAFFE) database, the output is analyzed and findings are compared in terms of recognition rate and time taken for processing. In the case of various facial expressions, it has been found that CS-LBP provides a higher detection rate than LBP has been presented [9].

HISTOGRAM OF ORIENTED GRADIENTS (HOG)

HOG is a feature descriptor utilized for the purpose of fruit detection in computer vision and image processing. In localized portions of an image, the technique counts instances of gradient orientation. This approach is close to that of histograms of edge orientation, descriptors of scale-invariant aspect transformation, and contexts of shape, but differs in that it is calculated on a dense grid of uniformly spaced cells and uses spatial contrast normalization overlap for better precision. Compute a Histogram of Oriented Gradients (HOG) includes five major steps:

1. global image normalization
2. computing the gradient image in x and y
3. computing gradient histograms
4. normalizing across blocks
5. flattening into a feature vector

The first stage is the optional global image normalization equalization, which is intended to reduce the impact of lighting effects. In reality, we use gamma (power law) compression, either by computing the square root or by recording each color channel. Image texture intensity is usually equal to the local surface illumination, so this compression tends to minimize the influence of local shadowing and lighting variations as shown as in figure (1).

Figure (1) global image normalization

The second stage calculates the gradients of the first order image. These capture the contour, silhouette and some texture information while providing additional resistance to variations in illumination. The locally dominant color channel is used, which gives a wide degree of color invariance. Variant approaches can also provide second-order image variants that serve as rudimentary bar detectors-a valuable function for capturing, e.g. bars such as frameworks in bicycles and limbs in humans as shown as in figure (2)

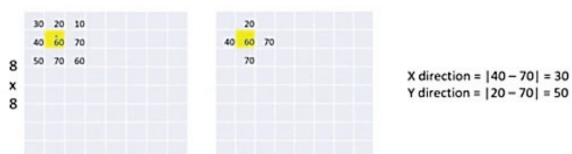

Figure (2) computing the gradient image in x and y

The third stage is intended to create an encoding that is adaptive to the quality of local images while being immune to subtle changes in pose or appearance. In the same way as the SIFT 2 function, the adopted method pools gradient orientation knowledge locally. The picture window is broken into "units" called tiny spatial regions. A local 1-D histogram of gradient or edge orientations is accumulated for each cell over all the pixels in the cell. The simple "orientation histogram" representation is generated by this combined cell-level 1-D histogram. The gradient angle spectrum is separated by each orientation histogram into a set number of predetermined bins. To vote on the orientation histogram, the gradient magnitudes of the pixels in the cell are used as shown as in figure (3).

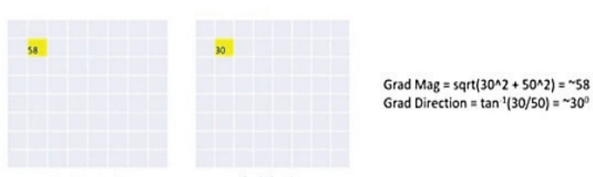

Figure (3) computing gradient histograms

The fourth step calculates the normalization of local groups of cells and the comparison normalizes their total responses before progressing to the next step. Normalization introduces greater invariance in color, shadowing, and edge contrast. This is achieved by accumulating a measure of local histogram "power" over local groups of cells that we call "blocks." The result is used to normalize any cell in the block. Usually, each cell is shared between a few blocks, but its normalizations are block-dependent and thus distinct. Thus, the cell appears multiple times in the final output vector with various normalizations. It can sound repetitive, but it increases performance. We are referring to the uniform block descriptors as Histogram of Oriented Gradient (HOG) descriptors as shown as in figure (4).

Figure (4) normalizing across blocks

The final stage extracts HOG descriptors for use in the window classifier from all blocks of a dense overlapping grid of blocks surrounding the detection window into a consolidated attribute vector.

I. Performance Evaluation using Confusion Matrix

The Confusion matrix is consisting of 2 x2 Table that containing four results it produces a classification, these are essential performance measures, like accuracy, specificity, and sensitivity which are derived from the confusion matrix. The confusion matrix is utilized to represent the test of the result prediction model. Each of rows stands for the predicted class which means the (Output Class), and the columns stand for the true class which means the (Target Class). In Table (1), The matrix of confusion is displayed, which is described as the different values and equations associated with them. Few of these equations are closely related to performance analysis.

Table (1): A Typical Confusion matrix [14].

Confusion matrix		Predicted	
		Negative	Positive
Actual	Negative	TN	FP
	Positive	FN	TP

The inputs of the confusion matrix have meaning in the context of the problem of data mining:

1. TN is the number of the prediction of true that in the case is negative,

2. FN is the number of predictions of false that a case positive,

3. TP It is a valid forecast number with a positive example,

4. FP Is the number of negative false predictions.

The following are the Basic measures derived from the confusion matrix:

1) Accuracy

ACC is determined as a number for all predictions of correct (TP + TN) divided by the total number of data sets (P + N). The best of accuracy equal to 1.0, while the worst equal 0.0. It can likewise be determined by 1 - error (ERR) as shown in equation (1).

$$ACC = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N} \quad (1)$$

2) Sensitivity (Recall or True Positive Rate)

Calculated the number of true positive (TP) predictions divided by a total of positive (P) predictions of this method called Sensitivity (SN) or likewise Recall or the True Positive Rate (TPR)(REC). The sensitivity equal to 1.0 is best, whereas the worst equal 0.0 as shown in equation (2).

$$SN = \frac{TP}{TP + FN} = \frac{TP}{P} \quad (2)$$

3) ***Specificity (True Negative Rate)***

Calculated the number of True Negative (TN) predictions divided by the total the number of negatives (N) this method called Specificity or True Negative Rate (TNR). The specificity equal to 1.0 is best, whereas the worst equal 0.0 as shown in equation (3).

$$SN = \frac{TN}{TN + FP} = \frac{TN}{N} \quad (3)$$

4. The Proposed Method

The proposed method consists of three main stages: first stage acquisition of the image, second stage extraction of brain cancer features, selection of more suitable features, classification to determine the correct category of the brain used precise identification of PNNs depends primarily on careful selection of features.

FEI Face Dataset

The FEI Face Database is a Brazilian facial database comprising a collection of facial photographs of 14 images taken for a total of 2,800 images for every 200 individuals. All images are colored and taken against a smooth white background in an upright forward position with a sideways rotation of approximately 180 degrees. The scale will differ by 10% and each image's original dimension is 640 x 480 pixels. All faces are overwhelmingly portrayed by FEI students and workers, who are between 19 and 40 years of age with varying looks, hairstyles, and decorations. The number of participants for men and women is almost the same and is equal to 100.

B. Pre-processing image

The first step in this work is the pre-processing of the image to enhance the image of the face. For the intention of viewing the image information properly, this method is used to boost the image since the photographs can often be captured under environments that are undesirable under terms of illumination, noise or the image size is very large and does not yield reasonable results. Converting the initial input templates from the standard RGB color format to the gray level color format helps in this process. This is done to enhance the perception of details in the models with a focus on the brightness factor, which makes it more precise and specific than the common format of the gray level. This improved Gaussian method was used, because of problems when Gaussian used a unit, the filters were improved by doubling the use of another Gaussian filter due to multiple iterations and different pixel density i.e. meaning that pixels with a density similar to the ones in the middle are included only to calculate an intense density value.

As a result, this technique preserves the edges, because the adjacent pixels placed on the other side of the edge for pixels close to the edges and therefore large differences in density appear in a blur when compared to the central pixel. To remove the influence of various lighting conditions. The color histogram of the grayscale image is equalized to eliminate the overall influence of the illumination in the setting so that the characteristics are more distinguishable from the classifier. Histogram equalization should be used for images of the face.

C. Histogram of Oriented Gradient (HOG) feature descriptor

In this work, after the image pre-processing, the features will be extracted using the HOG face classification algorithm, and the additional benefit of using this algorithm is that it will help in extracting the features of the image. This method is one of the best ways to extract strong features from the image because it depends on the vector and the angle to extract the features, as previously explained. This will aid in training and testing naive bays. HOG extracts the color feature and texture feature and forms a context feature. These features are stored in a mat file and are used to train naive Bayes.

D. Naive Bayes Classification

In this paper one of the methods of machine learning was used naive bayes. This method is to learn from the data and predict the class in which each class has a probability that is taken by inserting the features of the images that have been trained, and therefore the results that come out from them are high-resolution because they calculate the probability of error. Bayes theorem is shown in equation (4)

$$(A|B) = \frac{P\ (\mathrm{B|A}) * P(A)}{P(\mathrm{B})}$$

Where P(A) and P(B) are probabilities of observing A and B P(B|A) is the probability of observing event B given that ☐ is true.

Experimental Results

This method for face classification works best by machine learning, which gives very accurate results because it works at more than one level and after that, a decision is made after entering the strong feature that were extracted through HoG and this is explained through the results shown below.

Pre-processing stage: a. Pre-processing stage: This is the important stage during which the original image passes through the process of initialization through the use of the enhanced filter, through which we obtain a clear image empty of noise and with prominent edges.

b. Feature Extraction using HOG Algorithm: After pre-processing, feature descriptors are described in points of interest in both images, and this is the step by which the descriptor is calculated based on the areas cantered around the detected features. This includes converting the local pixel neighborhood into a small vector representation that allows comparison of neighbourhoods regardless of changes in face orientation or scale. Table (2) shows the extraction of features by the hog method, where each column represents its value to extract five vector (x, y, o, d, s) represents location, scale, orientation and Descriptor.

Table (2): Feature Vector of HoG.

Feature Vector of HoG				
x	**y**	**o**	**d**	**s**
9.587	9.08	0.01	0.00	8.0
11,391	7.57	0.01	0.00	7.9
6,571	9.95	0.02	0.00	7.8
7,575	9.34	0.02	0.00	7.8
9,623	8.30	0.01	0.00	7.8
6,230	10.19	0.01	0.01	7.9
9,645	8.29	0.01	0.00	7.9
6,575	9.95	0.02	0.00	7.8
7,896	9.16	0.01	0.00	7.9
8.258	9.36	0.01	0.00	7.9
10.258	9.29	0.01	0.00	8.0
11.467	7.86	0.01	0.00	8.0
12.560	7.48	0.01	0.00	7.9

c.naive bayes Classification: The result of naïve bayes classification of facial shown in Table (3) shown the evaluation performance of naïve bayes.

Table (3) Evaluation performance of naïve bayes

Face classification	
Sensitivity	97.3%
Specificity	97.7%
Accuracy	98.4%

Conclusion

In this paper, the powerful features will be extracted using the HoG algorithm and that is the image processing process where the image is converted to the grayscale image and then the noise is eliminated using the optimization algorithm of the gaussian filter to preserve the shape of the face and not lose the edges that are important in the feature extraction process, then the uniformity has preserved The lighting of all parts of the image using Histogram equalization, and then the strong features will be extracted using the algorithm and then classified using naive Bayes which the action was performed. The comparison is made by calculating the performance of the (Accuracy, Sensitivity, and Specificity) test for the FEL face data set and it is evident in Table (2) that the accuracy of facial performance is 98% .

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Conflict of Interest: None to declare.

Ethical Clearance: All experimental protocols were approved and all experiments were carried out in accordance with approved guidelines.

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