DEVELOPEMENT OF IMPROVED POSE INDEPENDENT FACE RECOGNITION ALGORITHM FROM VIDEO

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Abstract
Face recognition is the fundamental building block upon which all automated systems dealing with human faces are built. Exact face recognition is vital in many person-system user interfaces; the main importance is the precise technique to face identification. The design of a three-stage face identification system based on Haar Cascade Classifiers is proposed in this research. Pictures There are traditional Indian kathak and kuchipudi dances featured. Using 1000 photos for investigation, the suggested approach properly recognized 94 percent of the faces.
Keywords : *Face detection, Machine Learning, Open CV,Raspberry Pi, Haar Cascade Classifier*

1. Introduction

Human identity cannot exist without the face. Having a distinct personality trait is the most distinguishing characteristic of a person. An intriguing and demanding topic, face recognition has a significant influence on many essential applications.

Across several fields, including as law enforcement identification, the use of biometrics identification and verification procedures for bank accounts and security systems, and identification of one's self amid others. Face-recognition technology a simple job for humans, but a very different challenge for a robot. Computer. Only a little amount of information regarding human recognition has been gathered.so far as we've learned, how do we assess an image encoded in the brain and have internal characteristics (eyes, nose, mouth) employed for a good appearance (head shape, hairline). Is it possible to recognize another person's face using facial Brain researchers. Because we do not view the world as Our visual brain is tasked with putting together the disparate elements. Combining data from several sources to create meaningful patterns. Retrieving those faces that are most likely to be recognized by an algorithm is the primary goal of face-recognition .An image's significant characteristics are extracted, placed into an appropriate representation, and then classified.

A biometric system is nothing more than a pattern recognition system that uses the validity of a certain physiological or behavioral attribute possessed by the user to establish a personal identity. Individuals may be identified by measuring certain physical or behavioral traits and then evaluating them in comparison to other people's features. Decide how a person is identified is a major challenge in developing an effective system. A biometric system may or may not be appropriate in a given context. Verification (authentication) systems or identification systems [1] are the two options available.

Criminal identification and prison security have both made substantial use of biometrics, which is an emerging technology with rapid application potential. Biometric authentication is increasingly being employed in a broad variety of daily settings because to recent advancements in biometric sensors and matching algorithms. This approach may be used to complete purchases via the phone or the internet (electronic commerce and electronic banking). Biometric access and ignition may be utilized in automobiles as a biometric alternative for keys. An increase in national security concerns has prompted several countries [1] to begin using biometrics for border control and national identity cards.

Although studies on human face recognition were supposed to provide a reference on machine identification of faces, research on machine recognition of faces has grown independent of studies on human face recognition. Great acceptance and high collectability of face bio metric make it a widely recommended bio metric identification system in most of the application. During 1970's, standard pattern categorization methods, which employ measurements between features in faces or face profiles, were applied [4]. During the 1980's, efforts in facial recognition remained relatively steady. Since the early 1990's, research focus in machine identification of faces has expanded dramatically. The causes may be; An increase in focus on civilian/commercial research initiatives,

- The research on neural network classifiers with focus on real time computation and adaptability,
- The availability of real time hardware,
- The increased requirement for surveillance applications.

The most essential difficulty in face classification is how to encode the face into a structural code that can be utilized to identify the face. Geometrical local feature-based approaches and holistic template matching-based systems are the two major strategies utilized to detect human faces by computers. Hybrid techniques, which combine these two approaches, are also deployed. One technique, based on geometrical local characteristics, employs discrete local features (like eyes, nasolabial folds, lips, eyebrows, and hair) to retrieve and identify faces. In order to match faces based on these characteristics, classic statistical pattern recognition algorithms and/or neural network methodologies are applied. Elastic Bunch Graph Matching (EBGM) is a well-known geometrical-local feature-based approach. Another method that is conceptually similar to template matching is the use of global representations to identify faces [174]. Face pictures are examined holistically and characteristics gleaned from the whole facial region as a whole. Pattern classifiers are used to classify the image once the features have been extracted. One strategy to extract features from a holistic system is to use statistical approaches like Principal Component Analysis (PCA). It's possible to utilize PCA in the context of a face photograph, but this isn't a comprehensive approach. It doesn't matter whether method is utilized to deal with the problem of dimensionality while trying to recognize faces. Using proper methods, the size of the study area should be minimized. Learning occurs when over fitting occurs when more dimensions are added to a model. Computational complexity is a challenge when working with large datasets. In the following parts, we will discuss the results of the most significant studies. Algorithms based on statistics and neural networks are used to identify items.

2. Haar Cascading

An algorithm called Haar Cascading is used in machine learning to create a classifier based on thousands of images. Paul Viola and Michael Jones [5, 6] have presented the algorithm. The Haar feature-based cascade classifiers developed for object detection are the classifiers. As a result of this classifier's pursuit of machine learning,

In order to find elements in subsequent images, the cascade procedure is taught using photos. Recognition of people's faces and the emotions on their faces are also been shown to be true. The last step of the activity is to provide something constructive positive and negative images to the classification algorithm. Then, the features are outlined in the following manner:

A characteristic's value is determined by the sum of its component characteristics.

The pixels in the white rectangle were subtracted from those in the black rectangle to arrive at this result.

In which distinct people's faces are detected

Individuals found in many settings. No matter how big or little, the hair-like characteristic because of integral pictures, it is possible to compute in constant time.

3. Local Binary Patterns

Visual categorization on computer vision relies on the utilization of Local Binary Patterns (LBPs). Unlike the Texture Spectrum imitation put up in 1990, LBP is a unique instance. In 1994, LBP was first shown on a computer screen. Since then, it's been discovered to be a significant element in texture classification, as well. Micro-patterns are studied in a single shot with LBP operator. He then goes on to show a face-wide histogram of LBP that is encrypted to only micro-pattern situations. Face image is divided into m minor non-overlapping regions, such as R0, R1, and Rm.: For example, in the original LBP, each pixel is labeled by a threshold of three pixels around it. Edges, lines, and circles are all represented numerically on a certain scale. The coordinates of a point may be represented numerically by the number [3]. Because of this, it is conceivable a prior values collected from an image are used to identify items in the picture.

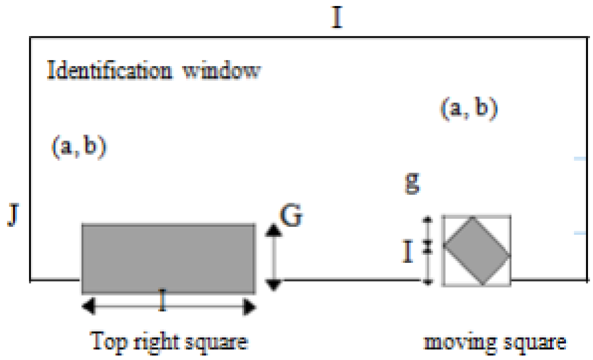

Figure 1: Top right and moving squares in the Identification window

These limitations remove 14 paradigm characteristics (see Figure 2), which may be wrapped in the two instructions and positioned any section of the detection window. This makes the establishment of an intensive pool of qualities. The possibilities would be conceptualized as the proportion of pixels aggregated beneath rectangles in black and white and armored to adjust for the dissimilarity of locales. It is worth mentioning that line selections are often recognized to be a combination of two rectangles: one incorporating both black and white, whereas the second merely a region of pure blackness.

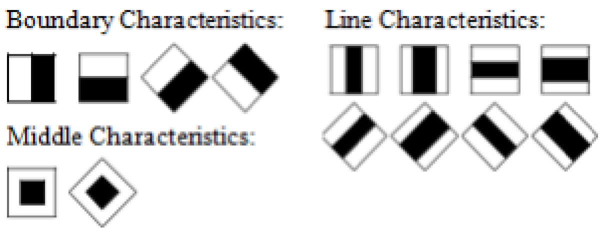

Figure 2: Prototypes of Haar-like characteristics

4. Algorithm Description

Image features and numerical variables have a significant impact on a classifier's performance. There is a direct correlation between training sample size, feature count, and the difficulty of a classifier. Classifier performance is not always improved by adding more features to a feature vector. The classifier's performance degrades as the number of training instances grows.

Tiny samples were used to select features. This kind of behavior is referred to as the "peaking phenomena". A limited training set indicates that the number of features cannot be enlarged at whim, and only a few must be picked. Despite this, it's hard to draw a direct link between the two. It is advised to utilize ten times as many training samples per class as the number of attributes to be selected [136]. If a classifier has a smaller number of attributes, it will run faster and use less memory. This may also have the opposite effect: a reduction in discriminating power and, as a consequence, a reduction in classification accuracy. There must be careful feature selection to achieve both low dimensionality and high classification accuracy.

In order to better understand how feature selection works, let me provide the following explanation: Select the subset with the lowest classification error if you have a lot of features. To put it another way, the selection criteria is: Pe = J. [3.18 pct]. incorrect categorisation Pe is denoted by In the direct approach of feature selection, all of the (d, m) possible subsets of size'm' are investigated using exhaustive search. The best subgroup with the greatest 'J' value has been selected. Due to the exponential expansion in the number of subsets, even with moderate values of'm' and 'd,' this technique is unable to function. The feature sets of various techniques are compared over time to see whether they are growing or shrinking. The Sequential Forward Selection (SFS) strategy maximizes the criterion function J by adding one feature at a time to the previously selected ones. You cannot remove features after they have been implemented. Sequential Backward Selection might provide similar outcomes (SBS). 'd' qualities are the first to be addressed, and they are subsequently eliminated one by one. Due to the smaller number of subgroups to search through, these sequential techniques are more efficient. It only searches (d-1) possible subsets for a set of size 2. As a consequence, feature subsets are layered and performance degrades as a result of the nested feature sets.

To circumvent the problem of feature nesting, utilize the "plus l - remove r" technique. A "l" number of SBS steps are next administered, followed by a "r" number of SFS steps. The selection procedure is repeated until all of the necessary features are found. By eliminating features that were previously implemented, the nesting effect may be prevented in this situation. A considerable amount of computation is required to obtain sufficient replies with the ideal selections of 'l' and 'r.'

5. Architecture Diagram

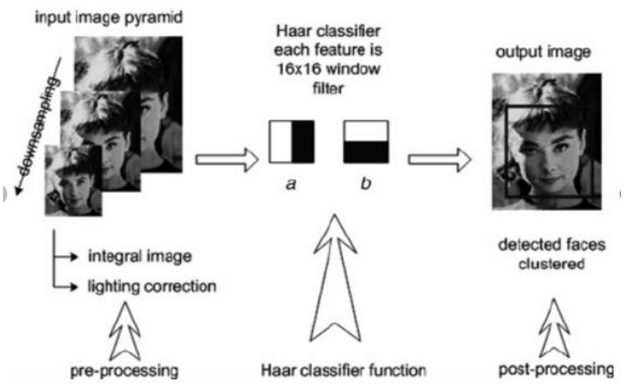

Figure 3: Face Recognition using Haar Classifier

6. Methodologies

Face detection In the field of technology Face detection is treated as the demanding and practically applied approach. The identification of each face present in an image is the major task of the face detection [11, 13, 14]. Here the implementation is done using MATLAB

i. Loading the input images.
ii. Converting the input images into gray scale images.
iii. Applying the Haar cascade and LBP classifier.
iv. Comparing both classifier based on the accuracy and time.

a Importing the required libraries
b Taking the images which are captured by the camera.
c To process the image through the classifiers it is converted into gray scale image.
d Image will be loaded using MATLAB
e By default, image will be loaded into BGR color space

The photos have been divided into two groups, '0' and '1'. "1" denoted every remaining category, whereas "0" represented the absence of any DR categories. Even though there are less photos in the No DR category, this would still be a good classification.

6.1 Haar cascade classifier

i Loading the input image using built in function cv2.imread(img_path), here the passing the image path as an input parameter
ii Converting it to gray scale mode and then displaying it
iii Loading the haar cascade classifier Fig. 3 represents the Haar like feature. It consists of edge feature and line feature. In the gray-scale image the white bar represents the pixels that are closer to the light source

Tracking objects consists of 3 steps. The HCC face \sdetector disrupts the complete frame in the 1st stage, integrating\sthe near positive results of HCC to produce a single consequence of detection. By employing 4-split cart as a bad classifier and position setting for 0.999 the appropriate tp ratio At each issue, the HCC chooses together with the conciliate Ada Boost. 2500 face images of kathak and kuchipudi dances are featured in the positive learning bundle for face HCC. The negative collection emerges by indiscriminately

Approximately 3,500 photos that do not feature any faces. Error IDs lower than 0.1 were called as true positive, and some were labeled as false positives

7. Results

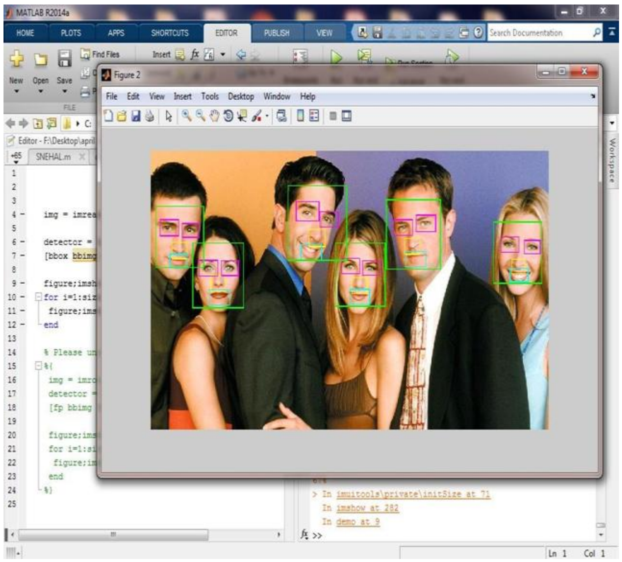

Fig 4 Multple face recognition using HAAR

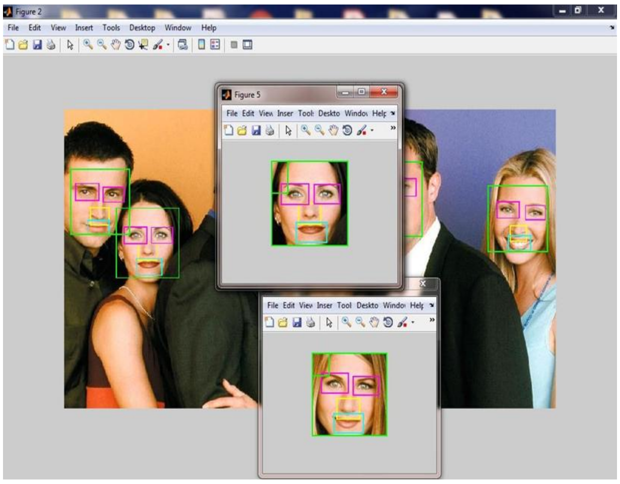

Fig 5 Faces feature extractions

8. Conclusion

The early detection of diabetic retinopathy can significantly help to successfully recover from this disease. But the clinical diagnosis process is both costly and time consuming. The analysis of medical images in computer vision has very fast processing capability and can be given better prediction accuracy. In this system we have designed a computational model to predict the Diabetic Retinopathy (DR). The major advantage of this system is that it is well suited for analyzing the data with preloaded input to detect the accurate result with greater performance and consume a less amount of time in processing and predicting the results. Hence it helps doctors in starting the treatments early for the patients and also it helps in diagnosing more patients within a shorter period of time.

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