

Occluded Face Recognition Using Machine Learning

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Abstract- A fascinating and intense issue nowadays is the difficult problem of identifying human faces when they are obscured by various obstructions. Due to a sizable occluded zone and a dearth of un-occluded portions, the capacity of most identification algorithms goes off dramatically. We describe a pre-processing approach for occluded faces that is effective and features-based to the fullest extent. Pose, lighting, age, emotions, and hair covering the face are among the 40 different occlusions that are included in the dataset. Edge-preserving enhancement and contrast measurement-correction for the occluded face pictures are part of the two simultaneous procedures used in the pre-processing step. Utilizing Gabor coefficients, Linear Binary Patterns based on Haar Wavelet components, and Histogram of Gaussian features, the finest textural characteristics are retrieved. The other set of characteristics used to represent the entire occluded face region is composed of wavelet components, color histograms, and statistical global features based on first order. In order to validate utilizing support vector machines, the study takes into account 100 celebrities from the CelebA dataset with posture and other occlusions. Compared to other well-known systems, the suggested efficient pre-processing and optimal features-based face recognition system exhibited increased classification accuracy in experiment analysis.

Keywords- Artificial Neural Networks (ANN), Support Vector Machines (SVM), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Gabor Wavelets, Elastic Bunch Graph Matching, Automatic Face detection (AFR)

INTRODUCTION

Since around 35 years ago, there have been significant advancements in the field of facial recognition, which have led to identification rates in the 90s. But the pandemic era has brought with it a new set of difficulties, making the process of acquiring a face subject to a broad variety of variances. These modifications are particularly for Automatic Face detection (AFR) employing machine learning methodologies, because occlusions of faces provide a very complicated object detection challenge in terms of efficiency, accuracy, and many other factors. When discussing face restrictions in terms of area of coverage being used or tested for facial recognition, the issues are further exacerbated by the similarity of the characteristics.

In light of the current situation, security research, particularly biometric face recognition, has thus become even more important during the current covidian epidemic, when wearing masks has added an additional difficulty to facial recognition research. A long-standing issue that poses a special difficulty not only for humans in daily life but also for facial running systems for diverse applications is the limited ability in the current era of computers to distinguish faces behind occlusions. Compared to other difficulties already present in nature, the issue of occlusion has received less attention from researchers. The purpose of our proposed research is to investigate face recognition in the presence of partial occlusions, with a focus on situations that could occur in daily life (such as wearing a mask or a scarf). A person's face is among their most significant biometric

characteristics. Faces of all kinds may be recognized easily by humans. To create a reliable computer system for facial identification, however, is a difficult undertaking. When compared to our own intrinsic capacity for face identification, the shortcomings of automated face recognition systems become very clear. Face recognition is a very difficult visual job that humans can do very instantly, and our own capacity for recognition is much stronger than anything a machine could ever hope to achieve. Under very poor lighting, from different angles, or from different perspectives, a human may recognize a known person. The 1960s saw the beginning of this field's study, but it hasn't been until lately that findings that are satisfactory have been attained.

A type of biometric software called facial recognition retains the information as a face print and uses mathematical mapping to represent a person's facial characteristics. The program employs Deep Learning algorithms to match a live capture or digital picture to the recorded facial print in order to confirm a person's identification. Facial recognition is now a realistic alternative for verification as well as identification thanks to the high-quality cameras in mobile devices. The technology, which employs machine learning to recognize, match, and identify faces, is utilized in a broad range of contexts, such as marketing and entertainment. One such device that employs face recognition to distinguish between players is the K bug motion gaming system.

STATE OF ART

In the [1] paper, concentrate on 3-D and biometric facial recognition systems. This page introduces the extent of India's recognition system. Using a digital picture or a video frame from a video source, a face recognition system may automatically recognize or confirm a person. Selected face characteristics from the image and a facial database can be compared as one method of doing this. It is frequently employed in security systems and is comparable to other biometric technologies like iris or fingerprint recognition systems.

In [2] paper, an effort to solve some of the most difficult facial aspects, including posture invariance, aging, illuminations, and partial occlusion. When applied to facial photographs, they are regarded as crucial components in face recognition systems. State-of-the-art face detection methods are also examined in this paper, including Eigen face, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Gabor Wavelets, Elastic Bunch Graph Matching, 3D morphable Models, and Hidden Markov Models. For the purpose of results analysis, they have also cited many testing face databases, including AT & T (ORL), AR, FERET, LFW, YTF, and Yale. But the goal of their study is to offer a thorough literature analysis on facial recognition and its uses.

In [3] paper, provide a thorough review of the most recent advancements in the industry. The deep network, optimization loss function, classification algorithm, train data collection, and deep network are the four key parts of a traditional deep face recognition system. The development of similar network architectures is covered in this study. The comparison of loss functions, classification methods, and face datasets is provided after that. Then, a comparison of contemporary facial recognition technologies is offered. Here, three benchmarking datasets with varying levels of complexity are used to discuss how well the systems perform. Additionally, an experimental investigation was done to assess the speed and accuracy of various publicly available facial recognition framework

In [3] paper, a COVID-19 disease classification model has been put out to categorize infected individuals from chest CT scans. Patients with COVID-19 infection are classified as infected (+ve) or not (+ve) using a convolutional neural network (CNN). Multi-objective differential evolution (MODE), in addition, is used to adjust CNN's starting parameters. The outcomes demonstrate that the suggested CNN model beats

competing models, such as ANN, ANFIS, and CNN models, in terms of accuracy, F-measure, sensitivity, specificity, and Kappa statistics by 1.9789%, 2.0928%, 1.8262%, 1.6827%, and 1.9276%, respectively.

In [4] paper, Convolutional Neural Network (CNN) with a transfer learning strategy was suggested as a way for automated facial recognition. the CNN with weights derived from the pre-trained VGG-16 model. For classification, the fully connected layer and softmax activation both receive the extracted features as input. The effectiveness of the suggested strategy is evaluated using two publicly accessible facial picture datasets, Yale and AT&T. The accuracy of facial recognition is 100% for the AT&T database and 96.5% for the Yale database. According to the findings, face recognition utilizing CNN and transfer learning provides greater classification accuracy than the PCA approach.

In [5] paper, based on photos of half-faces, a successful fractional face localization method using Alex-Net CNN has been presented. They highlighted the textural features and identified the main focal points. To discriminatively coordinate the two eliminated nearby capabilities, they presented an

PROPOSED WORK

With the help of course and fine features and a variety of descriptors, we have classified the occluded faces from the Celeb dataset using the conventional technique. The course features were made up of features made using GLCM, wavelet-based magnitude, and energy, while the fine features were made up of texture features made with HOG, wavelet, LBP, and Matched filter. A significant problem for any classifier network is the occlusion over the face area. As a result, the only cure was to enhance the faces' distinctive, high-quality traits. In order to get the greatest accuracy with such a low frequency dataset corresponding to each class, we experimentally adjusted the preprocessing and feature set while experimenting with a range

AlexNet CNN technique, and both the textural and geometrical data of neighborhood highlights were used for coordination. The distance between the corrected capabilities impacted the comparability of two appearances. They put their method to the test using four widely used face datasets, illustrating its strengths and limitations.

In [6] paper, introduced two novel preprocessing methods to lessen the lighting influence on photos of human faces. To remove light from the photos in the face database, the first suggested preprocessing approach employed Log transformation, Difference of Gaussian (DoG), and normalization. They employed Adaptive Histogram Equalization (AHE), Gaussian filtering, Log transformation, and normalization in the second suggested preprocessing approach. Here, they combined them and got rid of the lighting effect on the facial photographs. Principle Component Analysis (PCA) and Speed up Robust Features (SURF) were suggested here as feature extraction approaches. Here, Euclidean distance, SURF matching, and Support Vector Machine (SVM) were utilized for classification purposes. Here, they suggested six unique combinations of feature extraction, preprocessing, and classification algorithms.

of preprocessing and features that did not damage the textural and structural aspects of the faces. Another restriction imposed for this novel occluded face recognition was the small number of faces and high number of classes. Due to a wide feature set that includes both statistical and textural information, SVM was able to effectively categorize each group. The proposed occluded face identification system is depicted in the block diagram below.

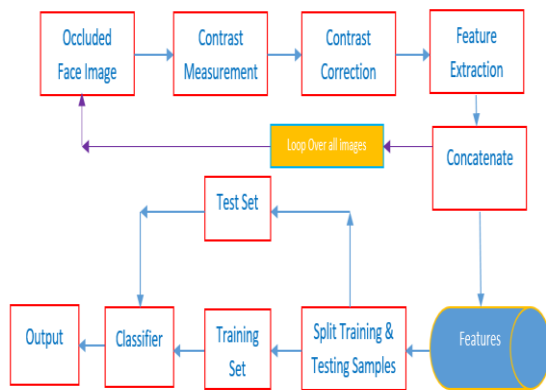


Fig. 2 Proposed System Architecture

Preprocessing Occlusion Acquired Image – According to the image normalization standard, the testing occluded picture must also undergo a specific amount of feature extraction processing in order for the features that are retrieved to be compared to the features included in the stacking auto encoded unique code given to each face.

Verification or Identification – In order to ensure face recognition and record the tuning parameters needed to repeat the process several times, the algorithm must conduct identity/unique code verification at this stage. With regard to the recognition application, we must work on verification, and the tuning parameters, such as orientation, call for testing CNN or RCNN in terms of accuracy, precision, and computational timings.

Algorithm Tested Data Analysis and Validation – This phase involves performing a graphical and numerical analysis to verify our findings in light of earlier reporting in order to draw conclusions and identify potential directions for our study.

DATASET



Fig.2 Sample of images from Celeb Dataset

RESULT

A total of 2528 characteristics for a picture were taken into account and normalized. The number of samples with a celebrity that were accessible ranged from 7 for folder 11 to a maximum of 403 for folder 91. In order to account for all the participants in the first 100 folders/classes, 5 samples from folder 11 were utilized for training, while the remaining 2 samples (30%) were used for testing. Table 2 lists the minimum samples taken from folders, the proportion of test samples, the eligible folders, the total test samples, and the accuracy attained using SVM with a gaussian kernel.

Minimum samples considered	Number of eligible folders	Percentage of test images selected randomly	Total number of test sample images	% Classification Accuracy
		30%		
100	19	30%	785	99
125	09		457	99
150	03		213	100
200	03		213	100

Table 2 – Classification Accuracy with respect to Minimum samples considered.

As previously said, out of 150 celebrities, only 100 have been taken into consideration. In the instance of [26], the dataset was enhanced to get an accuracy of about 93%; however, we employed the dataset in its original form without any enhancement, and even with this, our effective preprocessing and robust feature set enabled the fundamental machine learning tool SVM to achieve an accuracy of 98%. Using just 5 sample photos for training results in an accuracy of 93%, as shown in Table 2, and this accuracy rises when the number of minimal samples is increased. For such difficult scenarios, our suggested approach is clearly validated by an accuracy of 98% for 50 samples.

CONCLUSION

Despite the CelebA dataset's limited number of samples and classes and the difficulties associated with wide variations, our tried-and-true feature-based classification strategy utilizing SVM outperformed more cutting-edge techniques like deep learning and machine learning. The low count classes have no discernible impact on categorization, even though we did not enrich the dataset and used it in its unaltered state. Due to the best combination of coarse and fine features, the classifier was successfully trained with a feature dimension of about 4% (2528) of the entire picture dimension ($256 \times 256 = 65536$). An additional successful phase of this effort is the preprocessing (contrast enhancement and edge enhancement).

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