Mobile Face Recognition

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1. Introduction

1.1. Biometrics and Biometric system

Biometrics and biometric systems is the study of computing which helps us to identify and recognize human characteristics, such as fingerprint, face, iris, gait. According to Marcos Faundez-Zanuy the author of the paper Biometric security technology defines the biometric "it refers to the science involving the statistical analysis of biological characteristics" [1].Thus, we should refer to biometric recognition of people as those security applications that analyze human characteristics for verification and identification. Biometrics is a vast domain as it covers various recognition methods that use modalities like iris, face, fingerprint, muscle signals, gait etc. to provide access control and identify humans digitally. The applications of biometrics range from authentication workflows in handheld devices to maintaining identity records of criminals by the law enforcement agencies. Moreover, a biometric system is more reliable and secure as compared to token and data based systems as it attaches a unique anatomical and biological trait to the subject being identified and makes it harder to breach or spoof.

1.2. Face Recognition

Amongst all the biometric systems that are available today the most commonly observed biometric system is a Face recognition system. A human face is composed of many structures and characteristics making it a vital source of biological factors that can be fed to a robust algorithm to identify a subject. Face recognition systems are useful in many security application tasks due to following characteristics: it works in varying illumination conditions, it also works both with videos and images, it is robust and independent to the human in consideration may it be the hair color, gender and/or ethnicity and it also works with faces captured in different angles [2].

1.3. Project Description

There are many Face recognition approaches like local approaches, holistic approaches and Hybrid approaches. Our work focuses on local and holistic approaches together (Hybrid Approach). Local approaches include appearance based techniques which focus on facial expressions, occlusions and pose.The main goal is to extract distinctive features from a dataset of faces including expression, occluded and pose based images. Secondly holistic approaches include linear techniques that focus on using the whole face unlike only using a part of the face like eye or nose for recognition process. This approach converts the image into a matrix of pixels, this matrix then is converted to feature vectors to be converted into a low dimensional space [2]. So here we are trying to do feature level fusion by combining these two approaches.

The main objective of our work is to address the three research questions:

1. How do occlusions affect the performance of Face recognition system?
2. How do dark images and varying light conditions affect the recognition accuracy?
3. How important it is for the face in the right orientation for recognition and how face recognition works for different face poses?

We have predominantly used two techniques PCA and LBP on our classmates face recognition datasets (consisting 28 subjects) divided into three separate sub datasets namely Dark Images, Occluded Images and FacePose Images to answer the aforementioned questions.

2. Related Work

The literature related to our project proposes a method that divides an occluded face(face with sunglasses or mask) into two parts upper part and lower part.

It then runs feature extraction, dimensionality reduction(PCA) and SVM algorithm separately on the upper part and lower part.

Y. Su. Et al. proposed Two level SVM classifier in [4] then treats the above problem as a two class classification (occluded vs non-occluded)problem. The outputs of the first level SVM are decision values which indicate the probability of occluded or non-occluded. Using these decision values as the input data, the second level SVM are set up for the final results.

Experiments proposed in [4] use polynomial function as the kernel for SVM

Our approach is different from the [4] proposed approach where along with PCA we are also implementing LBP and doing a feature level fusion and then providing it to a SVM classifier to provide the result. Here LBP is used as it works good with occluded as well as dark images making the identification process better.

3. Methods

3.1. Datasets

The project uses three datasets namely (Occlusions, Dark Images and FacePose Images) which are sourced out from the frames related to three types of tasks: Tasks with occlusions on the subject's face, tasks where the subject is present in minimal source of illumination and the tasks where the subject is not facing the camera and facing in various directions.

3.2. Preprocessing

For all the above mentioned datasets we are following the below mentioned steps:

- Every image belonging to each type of dataset is read and converted to gray scale.
- Then all the images obtained are resized. Additionally, the images belonging to the Dark Images Dataset are brightened up.
- Once all the images are obtained they are divided into training and test sets using train_test_split() with a train size of 0.70.
- After splitting the train and test sets, they are scaled using StandardScaler() function provided by the Scikit Learn library.
- Post this the most important preprocessing step is performed where the obtained images in 4D are converted to 2 dimensional images using reshape() function provided by Scikit Learn library.This is the most important step as the feature extractors require 2D images to perform extraction.

3.3. Feature Extraction

For Feature Extraction the project uses PCA and LBP techniques:

3.3.1. Principal Component Analysis

- PCA is used to map the images in higher dimension to a lower dimension defined a subspace of basis vectors
- These vectors are called Eigen faces.
- So once the images are represented in the vector space instead of individual matrices, the data is standardized by subtracting the mean
- Then the covariance matrix C is computed. Then the Eigen values and Eigen vectors of C are computed.
- Once that is done the eigenvectors are mapped back to the image dimensions.
- Now as we are performing dimensionality reduction we only chose the top 30 eigenvectors corresponding with the highest variances/ top 30 eigenvalues.

3.3.2. Local Binary Pattern

- Local Binary pattern technique is useful when we need to deal with change in illumination conditions.
- In these scenarios we consider the local texture of the image.
- In LBP we have considered 1x3 neighborhoods,
- The values of these pixels are compared and a 2 bit binary string is generated.
- Local Histograms of these 2 bins are computed using these numbers.
- All these histograms are concatenated to generate the feature vector

3.4. Matching

For matching (prediction of the class/ subject), we are using SVC (Support Vector Classification) from scikit learn library. Support Vector Machine (SVM) is said to work best with images. We train the model on the template features and using svm.predict_proba() we are deriving per class probabilities and then we use the probability as scores.

3.5. Decision

For decision we predict the query image using the same SVC model that was used for matching and if the actual class matches the predicted class then we assign the score for this query to gen_scores (Genuine) list and all of the scores for other classes (which were not predicted) to imp_scores (Imposter) and if not then we attach all the scores for all classes to imp_scores list.

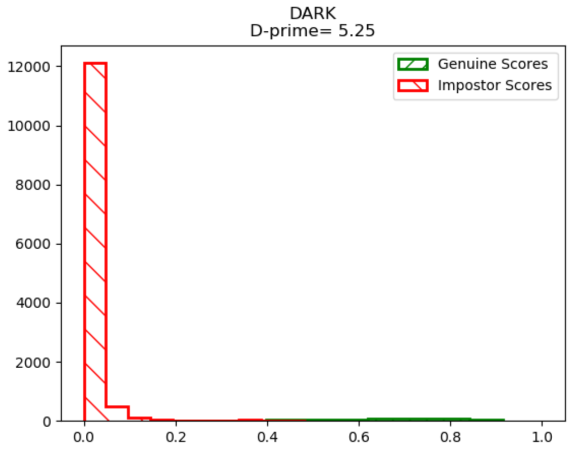
3.6. Level of Fusion

So the project performs feature Level fusion where we are fusing together the individual features obtained from PCA and LBP.

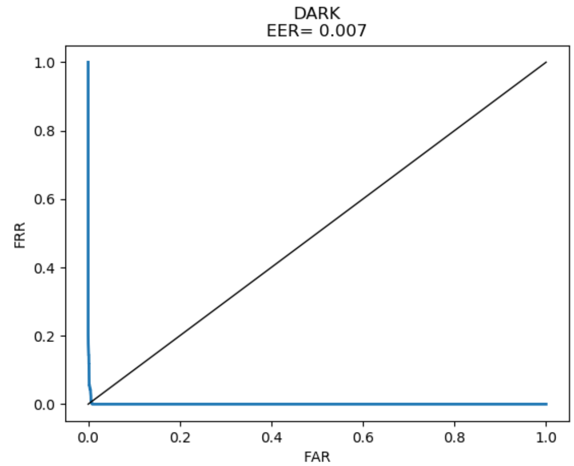
The fusion is performed by concatenating the feature arrays against the first axis.

4. Results

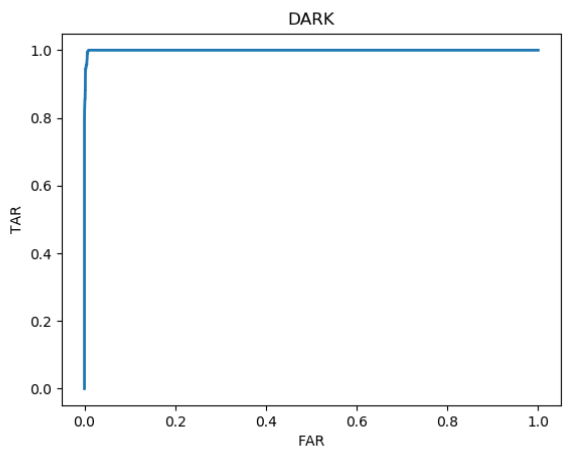
4.1. Dark Images



a. Score Distribution



b. DET Curve



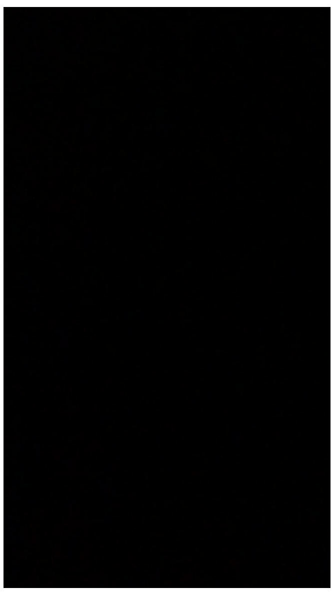
c. ROC Curve

No. Training Images : 1106
No. Test Images : 474
Accuracy : 93%

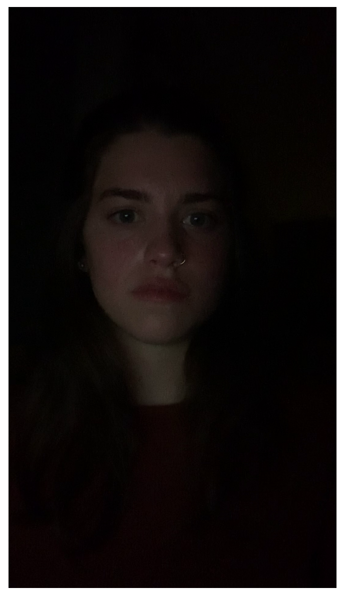
The D-Prime value of 5.25 from the score distribution indicates that the system performs well on Dark Images. It also shows that there is visible separation between the genuine and imposter score distributions making it a good classifier on Dark Images.

ROC curve has a sharp rise along the Y axis which implies that the true acceptance rate is increasing monotonically making it almost closer to a perfect classifier.

The DET curve shows the EER value of 0.007 that it almost closer to zero showing that the model is almost able to separate the two classes and has good measure of separability.

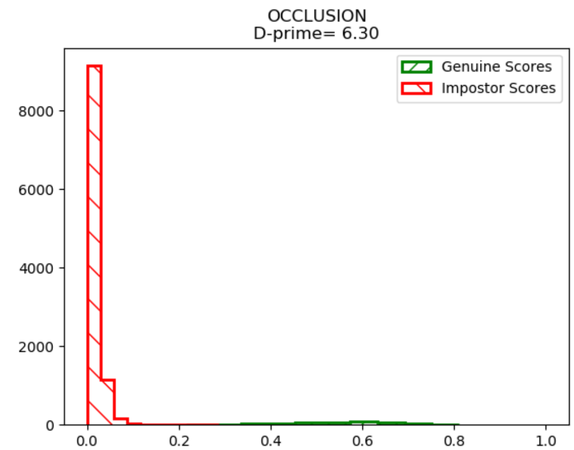


Incorrect : J_Strickland

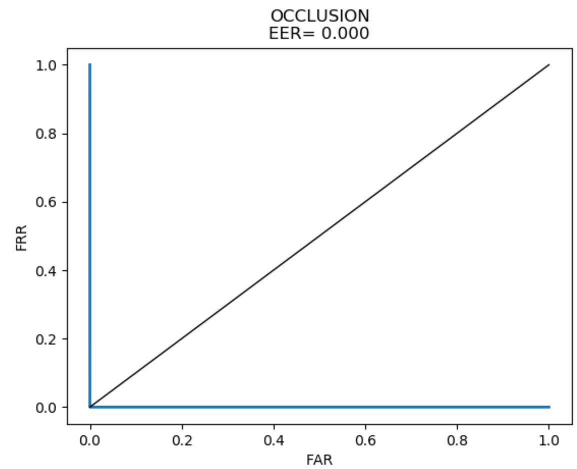


Correct : O_Heugel

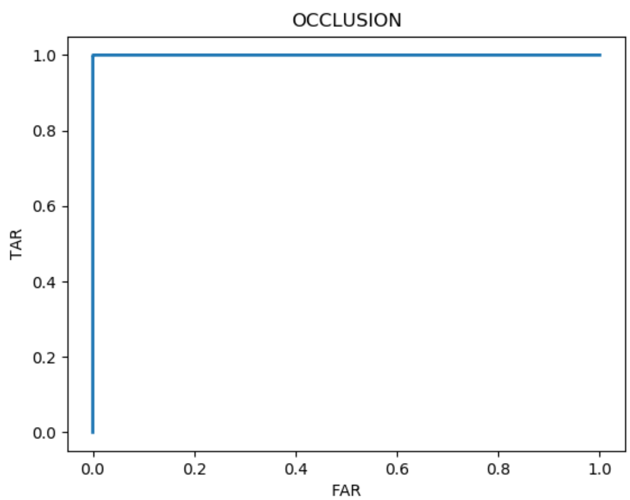
4.2. Occluded Images



a. Score Distribution



b. DET Curve



c. ROC Curve

No. Training Images : 909
No. Test Images : 390
Accuracy : 99%

Here, the D prime value of 6.30 for occluded images higher than the dprime value of dark images shows that the algorithm works better on them than the dark images dataset.

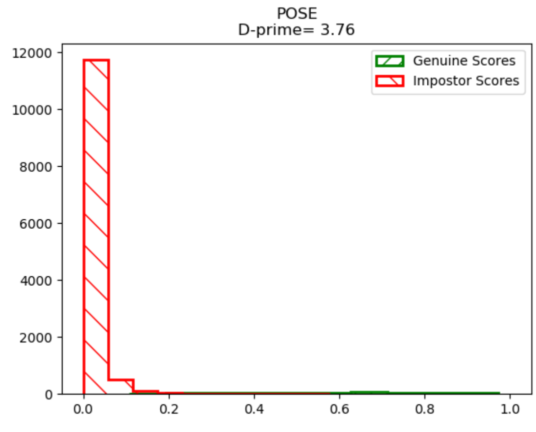
Also an accuracy of 0.99 shows that occlusions are handled well by the algorithm due to use of LBP for feature extraction.

Moreover the EER value of 0.000 makes it to almost a perfect example of classification.
And good separability between the genuine and imposter scores makes the process of choosing the right decision threshold easier.

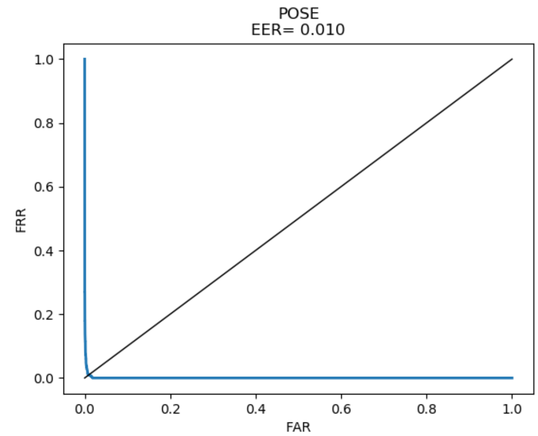
Incorrect : T_Nguyen

Correct : S_Bhadale

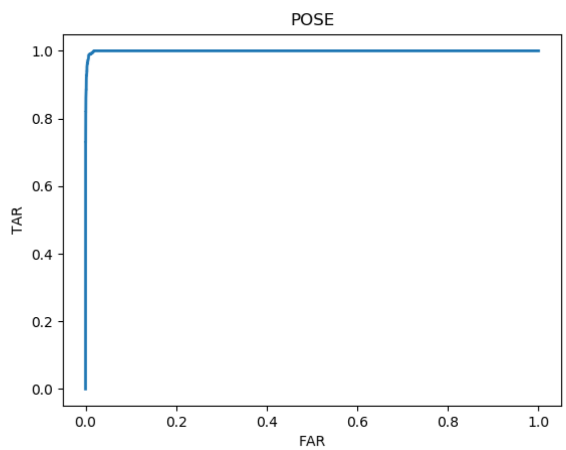
4.3. Pose Images



a. Score Distribution



b. DET Curve



C. ROC Curve

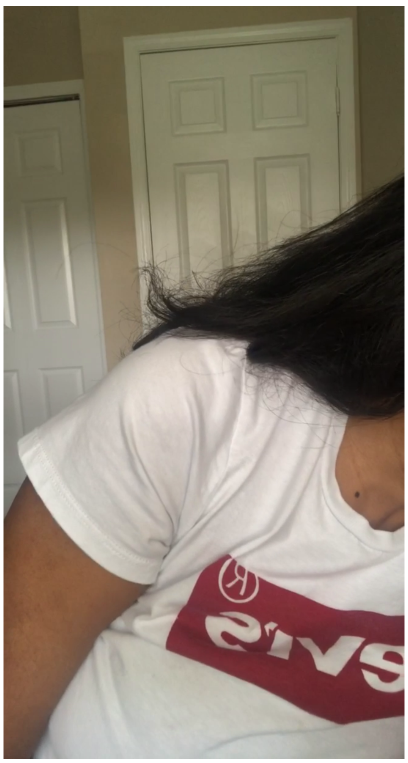
No. Training Images : 1069
No. Test Images : 459
Accuracy : 87%

In pose images dataset as the subject is not facing the camera directly so the accuracy drops to 0.87 reducing the performance. Although 0.87 is not a bad accuracy.

If we see the score distribution then we can observe the dprime value is the lowest (3.76) out of all the three when it comes to face pose image dataset as the feature extraction is not done the way it should be owing to different angles of the face.

The EER is observed to be 0.010 which is almost closer to zero making it a good classifier.

The ROC curve is monotonically increasing along the axis showing an increase in the True acceptance rate.



Incorrect : P_Lohar

Correct : C_Calderon

5. Conclusion

Overall, our system achieved a good performance on all the three datasets : Dark, Occluded and Pose. We extracted features using PCA (Principle Component Analysis) and LBP (Local Binary Pattern) and later fused the features together. We trained the dataset using SVM classifier, but we only trained the images on the specific folders so it was easy for the classifier to predict the class. Also, the frames, extracted were mostly similar as the subjects were asked to hold their poses for the video. So in future, we can try to train the image on a varied dataset so that we have images in all the orientation.

6. References

[1] Faundez-Zanuy, Marcos. (2006). Biometric security technology. Aerospace and Electronic Systems Magazine, IEEE. 21. 15 - 26. 10.1109/MAES.2006.1662038.

[ ] Kortli Y, Jridi M, Falou AA, Atri M. Face Recognition Systems: A Survey. Sensors (Basel). 2020;20(2):342. Published 2020 Jan 7. doi:10.3390/s20020342

[3] https://sightcorp.com/knowledge-base/face-matching-algorithms/#:~:text=In%20simple%20terms%2C%20a%20face,whether%20there%20is%20a%20match

[4] Y. Su, Y. Yang, Z. Guo and W. Yang, "Face recognition with occlusion," 2015 3rd IAPR Asian Conference on Pattern Recognition (ACPR), Kuala Lumpur, 2015, pp. 670-674, doi: 10.1109/ACPR.2015.7486587.