PERSPECTAI

PROJECT REPORT

PRESENTED BY

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TABLE OF CONTENTS

PRELIMINARY RESEARCH

- Preliminary research for implementing this model involved garnering knowledge of AI/ML based proctoring system and Face Recognition models

1. M. Ghizlane, B. Hicham and F. H. Reda, "A New Model of Automatic and Continuous Online Exam Monitoring," 2019 International Conference on Systems of Collaboration Big Data, Internet of Things & Security (SysCoBIoTS), Casablanca, Morocco, 2019, pp. 1-5, doi: 10.1109/SysCoBIoTS48768.2019.9028027. keywords: {Authentication;Monitoring;Face recognition;Servers;Smart cards;Face;Online exam;continuous authentication;machine learning;automatic monitoring},
2. Slusky, Ludwig (2020) "Cybersecurity of Online Proctoring Systems," Journal of International Technology and Information Management: Vol. 29: Iss. 1, Article 3.DOI: Goal 2
3. N. H. Barnouti, M. H. N. Al-Mayyahi and S. S. M. Al-Dabbagh, "Real-Time Face Tracking and Recognition System Using Kanade-Lucas-Tomasi and Two-Dimensional Principal Component Analysis," 2018 International Conference on Advanced Science and Engineering (ICOASE), Duhok, Iraq, 2018, pp. 24-29, doi: 10.1109/ICOASE.2018.8548818. keywords: {Face;Face recognition;Feature extraction;Webcams;Face detection;Classification algorithms;Training;Face Detection;Face Tracking;Face Recognition;Viola-Jones;KLT;2DPCA.},
4. R. S. V. Raj, S. A. Narayanan and K. Bijlani, "Heuristic-Based Automatic Online Proctoring System," 2015 IEEE 15th International Conference on Advanced Learning Technologies, Hualien, Taiwan, 2015, pp. 458-459, doi: 10.1109/ICALT.2015.127. keywords: {Conferences;E-learning;Proctoring system;Face Detection;Inference system;On-line examination},
5. Aurelia, S., Thanuja, R., Chowdhury, S. et al. AI-based online proctoring: a review of the state-of-the-art techniques and open challenges. Multimed Tools Appl 83, 31805–31827 (2024). https://doi.org/10.1007/s11042-023-16714-x
6. C. Ledig et al., "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 105-114, doi: 10.1109/CVPR.2017.19. keywords: {Image resolution;Signal resolution;Gallium nitride;Image reconstruction;Manifolds;Training;Network architecture},
7. Wang, X. et al. (2019). ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks. In: Leal-Taixé, L., Roth, S. (eds) Computer Vision – ECCV 2018 Workshops. ECCV 2018. Lecture Notes in Computer Science(), vol 11133. Springer, Cham. https://doi.org/10.1007/978-3-030-11021-5_5

RELATED WORK

- Proposed model draws inspiration from the work of the following researchers:

1. C. Song, Z. He, Y. Yu and Z. Zhang, "Low Resolution Face Recognition System Based on ESRGAN," 2021 3rd International Conference on Applied Machine Learning (ICAML), Changsha, China, 2021, pp. 76-79, doi: 10.1109/ICAML54311.2021.00024. keywords: {Image recognition;Art;Databases;Face recognition;Superresolution;Machine learning;Generative adversarial networks;Face detection;Face Recognition;YOLO;Super-resolution reconstruction;ESRGAN},
2. Yang, Jian & Zhang, David & Frangi, Alejandro & Yang, Jing-yu. (2004). Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence. 26. 10.1109/TPAMI.2004.1261097.
3. Koch, G.R. (2015). Siamese Neural Networks for One-Shot Image Recognition.
4. V. D. M. Nhat and S. Lee, "Kernel-based 2DPCA for Face Recognition," 2007 IEEE International Symposium on Signal Processing and Information Technology, Giza, Egypt, 2007, pp. 35-39, doi: 10.1109/ISSPIT.2007.4458104. keywords: {Face recognition;Principal component analysis;Covariance matrix;Kernel;Independent component analysis;Feature extraction;Face detection;Lighting;Signal processing;Information technology;PCA;Kernel PCA;2DPCA;Face Recognition},
5. Turk, M.A. and Pentland, A.P., 1991, January. Face recognition using eigenfaces. In Proceedings. 1991 IEEE computer society conference on computer vision and pattern recognition (pp. 586-587). IEEE Computer Society.

THEORISED MODEL

- The theorised model aims to build the lightest weight face recognition model with an accuracy better than the present deployed model of PerspectAI that gives 75-85% accuracy.
- This could in future also cater to the needs of PerspectAI's goal to deploy the face verification model on the system of the candidate instead of server processing.
- The theorised model also aims to handle images taken by the candidate's webcam, typically of low resolution through upscaling.
- The images are first preprocessed by applying a face detection model of Viola-Jones.This gives us the face Region of Interest or ROI
- The ROI is the upscaled using ESRGAN and resized to a resolution of 64x64 px, also converted to grey scale.
- The model is then trained by taking an equal number of positive pairs and negative pairs of candidates. Generated 21,248 training pairs with 10,624 positives and 10,624 negatives.
- Model also generated 5160 validation pairs with 2580 positives and 2580 negatives; 8112 test pairs with 4056 positives and 4056 negatives
- All pairs generated with corresponding labels '1' if the pair is of images of the same subject and '0' if the pair is of images of different subjects.
- Then we apply 2DPCA to the stack of training images compute the covariance matrix and extract the desired number of top eigen vectors (k=30 diff values of k experimented with, more on page 8)
- Then we iterate through the training pairs and project the images onto the subspace defined by the extracted eigen vectors
- We concatenate the arrays of the projection of images and append it finally to an array named train features
- Then fit the model into a Multi Layer Perceptron Classifier to perform binary classification. '1' if the images are of the same person and '0' if the images are not of the same person.(Different Classifiers were experimented with, more on page 8)

ML PIPELINE

01

Data preprocessing.

- Viola Jones Algorithm.
- Upscaling through ESRGAN.
- Resize and convert to grey scale.
- Make equal number of positive and negative pairs from train, val and test data.
- Assign appropriate labels.

02

Feature extraction.

- Apply 2DPCA and obtain the top eigen vectors with the help of training images.
- Project each image onto the subspace defined by the top eigen vectors obtained.
- Concatenate the arrays of image projections into a single array and append to the final training features array

03

Model Training.

- Fit the training features with their corresponding labels into an MLP classifier
- MLP classifier with hidden layer sizes= (256,128,64), max_iterations as 1000, validation_fraction=0.1 and learning rate=0.001
- XGB Classifier objective='binary:logistic', n_estimators=8000

04

Model Evaluation and Hyperparameter Tuning

- Calculating validation accuracy and validation precision
- Calculating test accuracy and test precision
- Hyper parameter tuning of the two promising models- XGB classifier and MLP classifier to find the best possible accuracy and precision

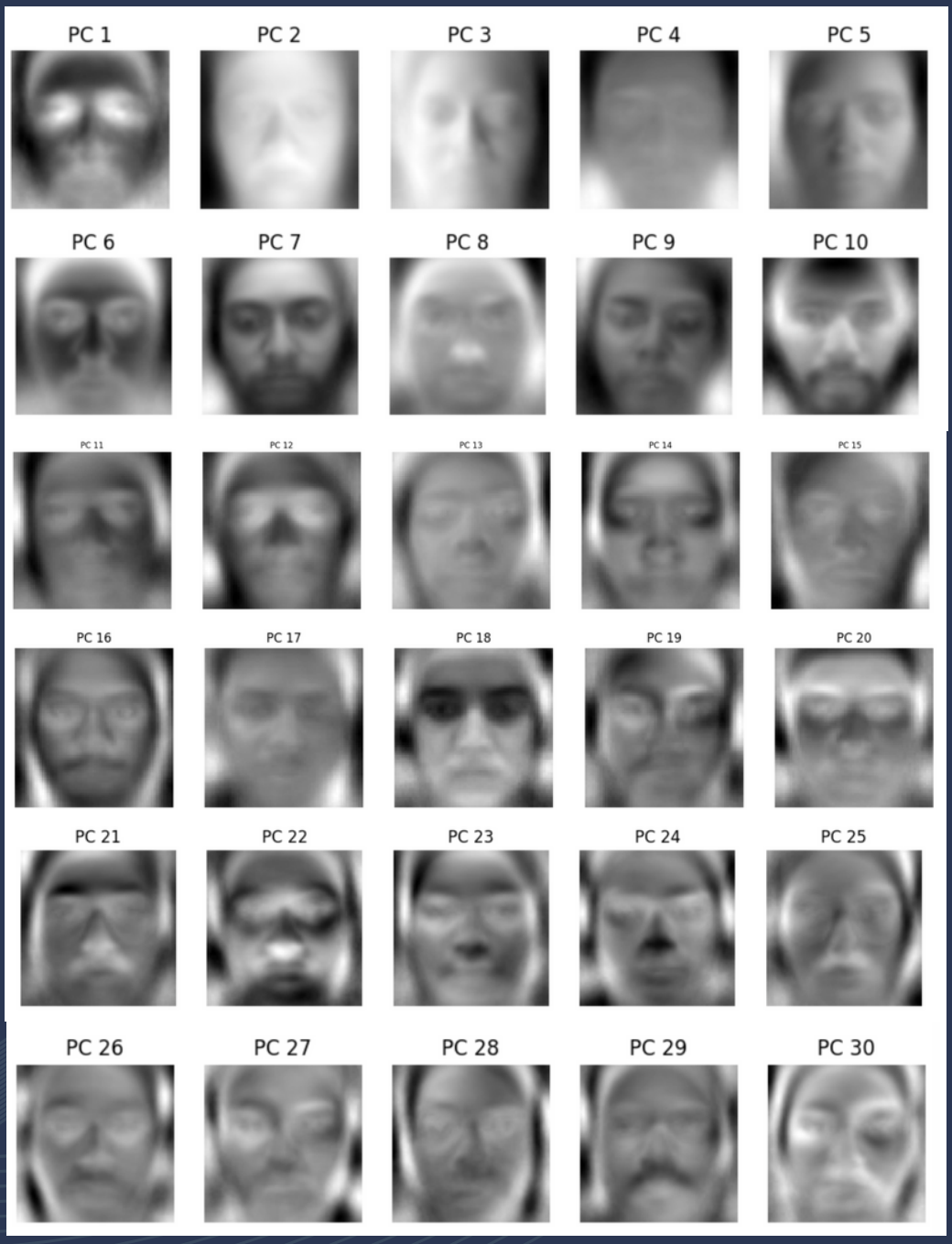
05

Exploring promising areas.

- Benefits of upscaling could be further optimised if the size rescaling of images after upscaling the ROI is made to 256x256 px or 128x128 px instead of 64x64 px as we are failing to capture the benefits made through upscaling.
- More training data could improve the model training, subsequently its accuracy on unknown data
- We could try other face detection models like YOLO,MTCNN

FEATURE EXTRACTION:VISUALIZED

These are the thirty eigen vectors that were extracted from the training images.When an image is processed in test data or validation data.The images is projected on to the subspace created by these eigen vectors and the dot product of each image with these following eigen vectors is taken.
We then get a coefficient for each 'PC' Principle Component signifying its similarity or contribution to constitute the image given. This array of coefficients of image 1 is concatenated with the array of images of image 2. This combined feature coefficient array is passed on to the classifier to verify if both images belong to the same person or not.



Different values of k were tested-10,15,20,25,30,35.
The best accuracy was obtained at k=30

MODEL COMPARISONS AND BENCHMARK SCORES

The Model was fitted on various types of classifiers (to obtain Binary classification: 0 if the person in the second image doesn't match person in first and 1 if they match.The following classifiers appeared to look the most promising.

1.MLP Classifier
2.Random Forest Classifier
3.Gradient Boosting Machine Classifier
4.KNN Classifier

After Hyperparameter tuning parameters for each model proved to be effective and these are the precision and accuracy values respectively.

1.MLP CLASSIFIER

```
In [62]: from sklearn.neural_network import MLPClassifier
mlp_classifier = MLPClassifier(hidden_layer_sizes=(256,128, 64), activation='relu',
                               solver='adam', random_state=42, max_iter=1000, verbose=True,
                               learning_rate='adaptive',early_stopping=False,alpha=0.1,
                               learning_rate_init=0.001,n_iter_no_change=500,validation_fraction=0.1)
```

```
MLPClassifier
MLPClassifier(alpha=0.1, hidden_layer_sizes=(256, 128, 64),
              learning_rate='adaptive', max_iter=1000, n_iter_no_change=500,
              random_state=42, verbose=True)
```

```
In [50]: val_features = []
for img1, img2 in tqdm(val_pairs, desc='Validation pairs'):
    proj_img1 = project_2dpca(img1.flatten(), eig_vecs)
    proj_img2 = project_2dpca(img2.flatten(), eig_vecs)
    val_features.append(np.concatenate([proj_img1, proj_img2]))
val_features = np.array(val_features)
```

```
Validation pairs: 100% 5160/5160 [00:00<00:00, 9134.79it/s]
```

```
In [51]: val_pred = mlp_classifier.predict(val_features)
val_accuracy = accuracy_score(val_labels, val_pred)
val_precision=precision_score(val_labels, val_pred)

print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Precision: {val_precision:.9f}")
```

```
Validation Accuracy: 0.8703
Validation Precision: 0.912386707
```

```
In [52]: test_features = []
for img1, img2 in tqdm(test_pairs, desc='Test pairs'):
        proj_img1 = project_2dpca(img1.flatten(), eig_vecs)
        proj_img2 = project_2dpca(img2.flatten(), eig_vecs)
        test_features.append(np.concatenate([proj_img1, proj_img2]))
test_features = np.array(test_features)
```

```
Test pairs: 100% 8112/8112 [00:00<00:00, 10745.01it/s]
```

```
In [53]: test_pred = mlp_classifier.predict(test_features)
test_accuracy = accuracy_score(test_labels, test_pred)
test_precision=precision_score(test_labels, test_pred)

print(f"Test Accuracy: {test_accuracy}")
print(f"Test Precision: {test_precision:.9f}")
```

```
Test Accuracy: 0.9323224852071006
Test Precision: 0.913268914
```

2.Random Forest Classifier

In [55]:
```
rf_classifier = RandomForestClassifier(n_estimators=100000, random_state=77)

rf_classifier.fit(train_features, train_labels)
```

In [56]:
```
val_features = []
for img1, img2 in tqdm(val_pairs, desc='Validation pairs'):
    proj_img1 = project_2dpca(img1.flatten(), eig_vecs)
    proj_img2 = project_2dpca(img2.flatten(), eig_vecs)
    val_features.append(np.concatenate([proj_img1, proj_img2]))
val_features = np.array(val_features)
```

```
Validation pairs: 100% 5160/5160 [00:02<00:00, 2535.95it/s]
```

In [57]:
```
val_pred = rf_classifier.predict(val_features)
val_accuracy = accuracy_score(val_labels, val_pred)
val_precision=precision_score(val_labels, val_pred)

print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Precision: {val_precision:.9f}")
```

```
Validation Accuracy: 0.8308
Validation Precision: 0.935681470
```

In [58]:
```
test_features = []
for img1, img2 in tqdm(test_pairs, desc='Test pairs'):
        proj_img1 = project_2dpca(img1.flatten(), eig_vecs)
        proj_img2 = project_2dpca(img2.flatten(), eig_vecs)
        test_features.append(np.concatenate([proj_img1, proj_img2]))
test_features = np.array(test_features)
```

```
Test pairs: 100% 8112/8112 [00:02<00:00, 3460.08it/s]
```

In [59]:
```
test_pred = rf_classifier.predict(test_features)
test_accuracy = accuracy_score(test_labels, test_pred)
test_precision=precision_score(test_labels, test_pred)

print(f"Test Accuracy: {test_accuracy}")
print(f"Validation Precision: {val_precision:.9f}")
```

```
Test Accuracy: 0.9309664694280079
Validation Precision: 0.935681470
```

3.XGB Classifier

In [79]:
```
xgb_classifier = xgb.XGBClassifier(
    objective='binary:logistic',  # For binary classification
    max_depth=3,                  # Maximum depth of the tree
    learning_rate=0.1,            # Learning rate
    n_estimators=8000,             # Number of trees (boosting rounds)
    subsample=0.8,                # Subsample ratio of the training instance
    colsample_bytree=0.8,         # Subsample ratio of columns when construc
    random_state=42,
    eval_metric='error',
    grow_policy='lossguide'
    # Random state for reproducibility
)
```

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='error', feature_types=None,
              gamma=None, grow_policy='lossguide', importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=8000, n_jobs=None,
```

In [65]:
```
val_features = []
for img1, img2 in tqdm(val_pairs, desc='Validation pairs'):
    proj_img1 = project_2dpca(img1.flatten(), eig_vecs)
    proj_img2 = project_2dpca(img2.flatten(), eig_vecs)
    val_features.append(np.concatenate([proj_img1, proj_img2]))
val_features = np.array(val_features)
```

```
Validation pairs: 100% 5160/5160 [00:01<00:00, 4688.51it/s]
```

In [66]:
```
val_pred = xgb_classifier.predict(val_features)
val_accuracy = accuracy_score(val_labels, val_pred)
val_precision=precision_score(val_labels, val_pred)

print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Precision: {val_precision:.9f}")
```

```
Validation Accuracy: 0.8864
Validation Precision: 0.920675105
```

In [67]:
```
test_features = []
for img1, img2 in tqdm(test_pairs, desc='Test pairs'):
        proj_img1 = project_2dpca(img1.flatten(), eig_vecs)
        proj_img2 = project_2dpca(img2.flatten(), eig_vecs)
        test_features.append(np.concatenate([proj_img1, proj_img2]))
test_features = np.array(test_features)
```

```
Test pairs: 100% 8112/8112 [00:04<00:00, 3071.34it/s]
```

In [68]:
```
test_pred = xgb_classifier.predict(test_features)
test_accuracy = accuracy_score(test_labels, test_pred)
test_precision=precision_score(test_labels, test_pred)

print(f"Test Accuracy: {test_accuracy}")
print(f"Test Precision: {test_precision:.9f}")
```

```
Test Accuracy: 0.9277613412228797
Test Precision: 0.906132959
```

4.KNN Classifier
(with k=20 i.e only using top 20 eigen vectors)

```
In [71]: from sklearn.neighbors import KNeighborsClassifier
         knn = KNeighborsClassifier(n_neighbors=12)
         knn.fit(train_features, train_labels)
```

Out[71]:

KNeighborsClassifier

KNeighborsClassifier(n_neighbors=12)

```
In [72]: val_features = []
         for img1, img2 in tqdm(val_pairs, desc='Validation pairs'):
             proj_img1 = project_2dpca(img1.flatten(), eig_vecs2)
             proj_img2 = project_2dpca(img2.flatten(), eig_vecs2)
             val_features.append(np.concatenate([proj_img1, proj_img2]))
         val_features = np.array(val_features)
```

Validation pairs: 100% 5160/5160 [00:00<00:00, 13902.19it/s]

```
In [73]: val_pred = knn.predict(val_features)
         val_accuracy = accuracy_score(val_labels, val_pred)
         val_precision=precision_score(val_labels, val_pred)
         print(f"Validation Accuracy: {val_accuracy:.4f}")
         print(f"Validation Precision: {val_precision:.4f}")
```

```
Validation Accuracy: 0.8198
Validation Precision: 0.7708
```

```
In [75]: test_features = []
         for img1, img2 in tqdm(test_pairs, desc='Test pairs'):
                 proj_img1 = project_2dpca(img1.flatten(), eig_vecs2)
                 proj_img2 = project_2dpca(img2.flatten(), eig_vecs2)
                 test_features.append(np.concatenate([proj_img1, proj_img2]))
         test_features = np.array(test_features)
```

Test pairs: 100% 8112/8112 [00:00<00:00, 16801.24it/s]

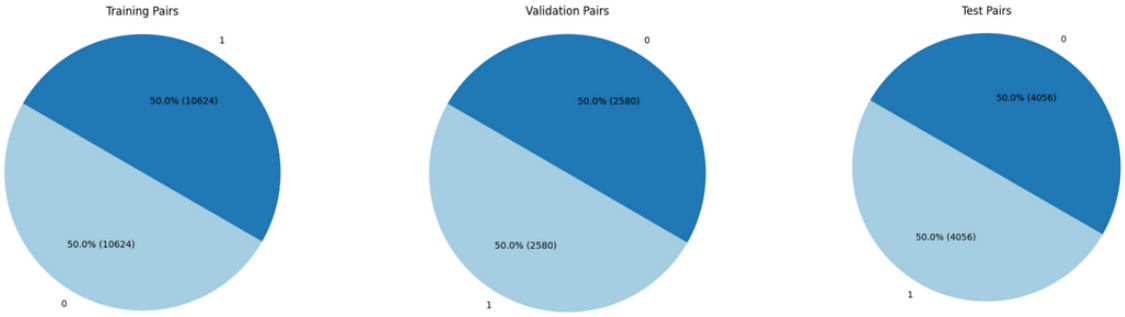
```
In [76]: test_pred = knn.predict(test_features)
         test_accuracy = accuracy_score(test_labels, test_pred)
         test_precision=precision_score(test_labels, test_pred)

         print(f"Test Accuracy: {test_accuracy}")
         print(f"Validation Precision: {val_precision:.4f}")
```

```
Test Accuracy: 0.8292652859960552
Validation Precision: 0.7708
```

MODEL	MLP Classifier	Random Forest Classifier	XGB Classifier	KNN Classifier (k=20)
VALIDATION ACCURACY	87.03%	83.08%	88.64%	81.98%
VALIDATION PRECISION	91.23%	93.56%	92.06%	77.08%
TEST ACCURACY	93.23%	93.09%	92.77%	82.92%
TEST PRECISION	91.32%	93.56%	90.61%	77.08%

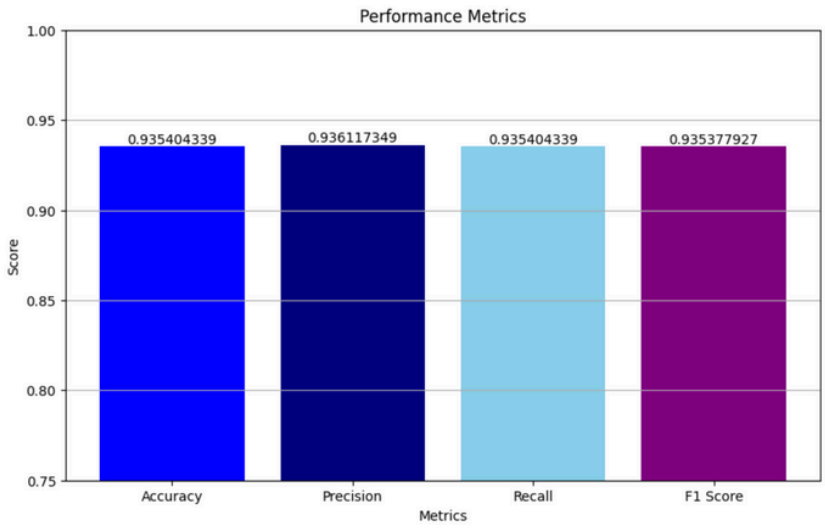
METRICS AND ANALYTICS



Equal Pairs of negatives and positives were made of all three types of data: train, test and validation.
The process of generating pairs was as follows:

1. Iterate through all person folders.
2. Generate positive pairs from each folder (+ve pairs made)
3. Iterate though all person folders
4. Chose a random folder from other folders
5. Choose a random image and generate -ve pairs.
6. Ensuring equal number positive and negative pairs by using random.sample

Among the classifiers providing the highest accuracy, the metrics for the MLP classifier are as follows:




```
from sklearn.metrics import classification_report

# Print classification report for detailed metrics
print(classification_report(test_labels, test_pred))
```

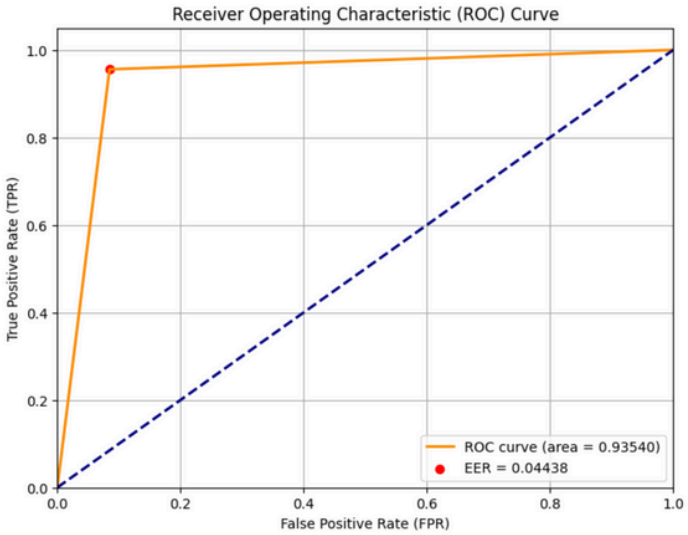
```
              precision    recall  f1-score   support

           0       0.95      0.92      0.93      4056
           1       0.92      0.96      0.94      4056

    accuracy                           0.94      8112
   macro avg       0.94      0.94      0.94      8112
weighted avg       0.94      0.94      0.94      8112
```

For class 0, it achieved a precision of 0.95, a recall of 0.92, and an F1-score of 0.93, based on 4056 positive test samples. For class 1, it attained a precision of 0.92, a recall of 0.96, and an F1-score of 0.94, also based on 4056 negative test samples. The overall accuracy of the MLP classifier was 0.94 across 8112 samples.

METRICS AND ANALYTICS

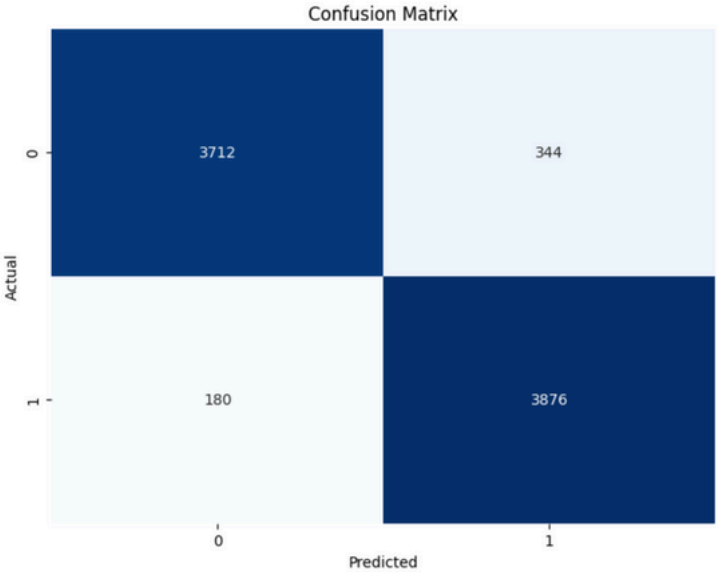


AUC-ROC of 0.93540 indicates that the model is performing very well in distinguishing between the two classes it is predicting.

he EER of 4.438% signifies that the system achieves an equal balance between incorrectly accepting legitimate users and rejecting authorized users.

The plotted confusion matrix indicates that out of 8112 test pairs:

- **True Positives** were 3876 in number
- **True Negatives** were 3712 in number.
- **False Positives** were 344 in number.
- **Flase negatives** were 180 in number



Computational Efficiency

```
Average Inference Time: 0.0385644 seconds
Peak Memory Usage: 23.77 MB
Average CPU Utilization: 19.79%
```

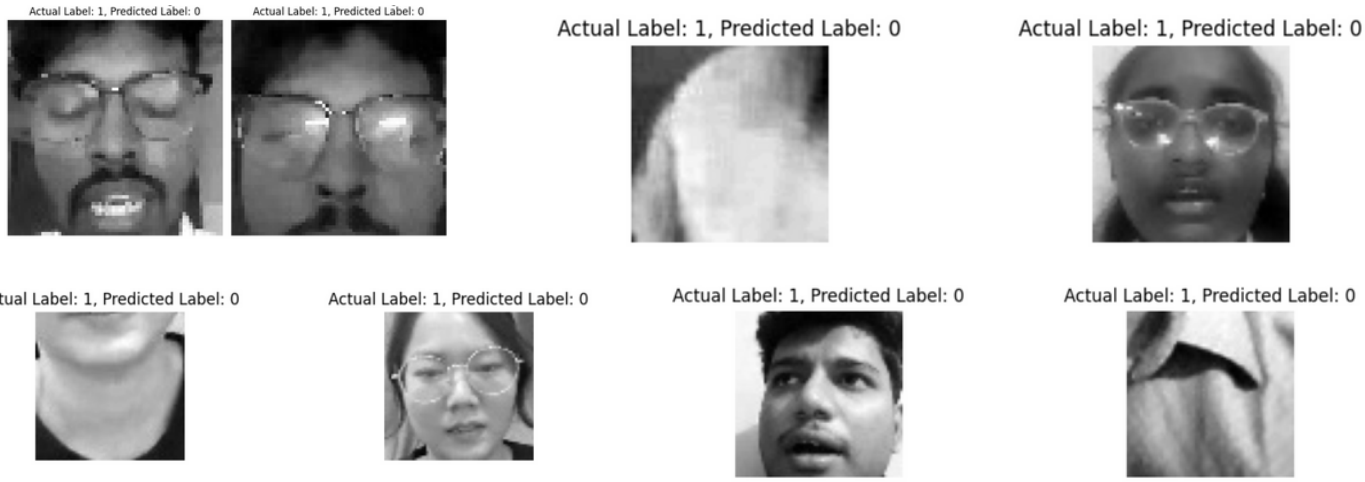
To evaluate the performance of the MLP classifier, a thorough assessment of its inference time, memory usage, and CPU utilization was conducted. First, the inference time was measured by running predictions on the test features 100 times, recording the duration for each run, and calculating the average. The results showed an average inference time of approximately 0.038 seconds.

Next, memory usage was assessed using the tracemalloc module. Memory allocation was traced before running predictions, and both the current and peak memory usage were recorded after the predictions.

The peak memory usage was found to be approximately 23.77 MB. Lastly, CPU utilization was measured by sampling the CPU usage during predictions over ten intervals, each lasting 0.1 seconds. The average CPU utilization was determined to be approximately 19.79%.

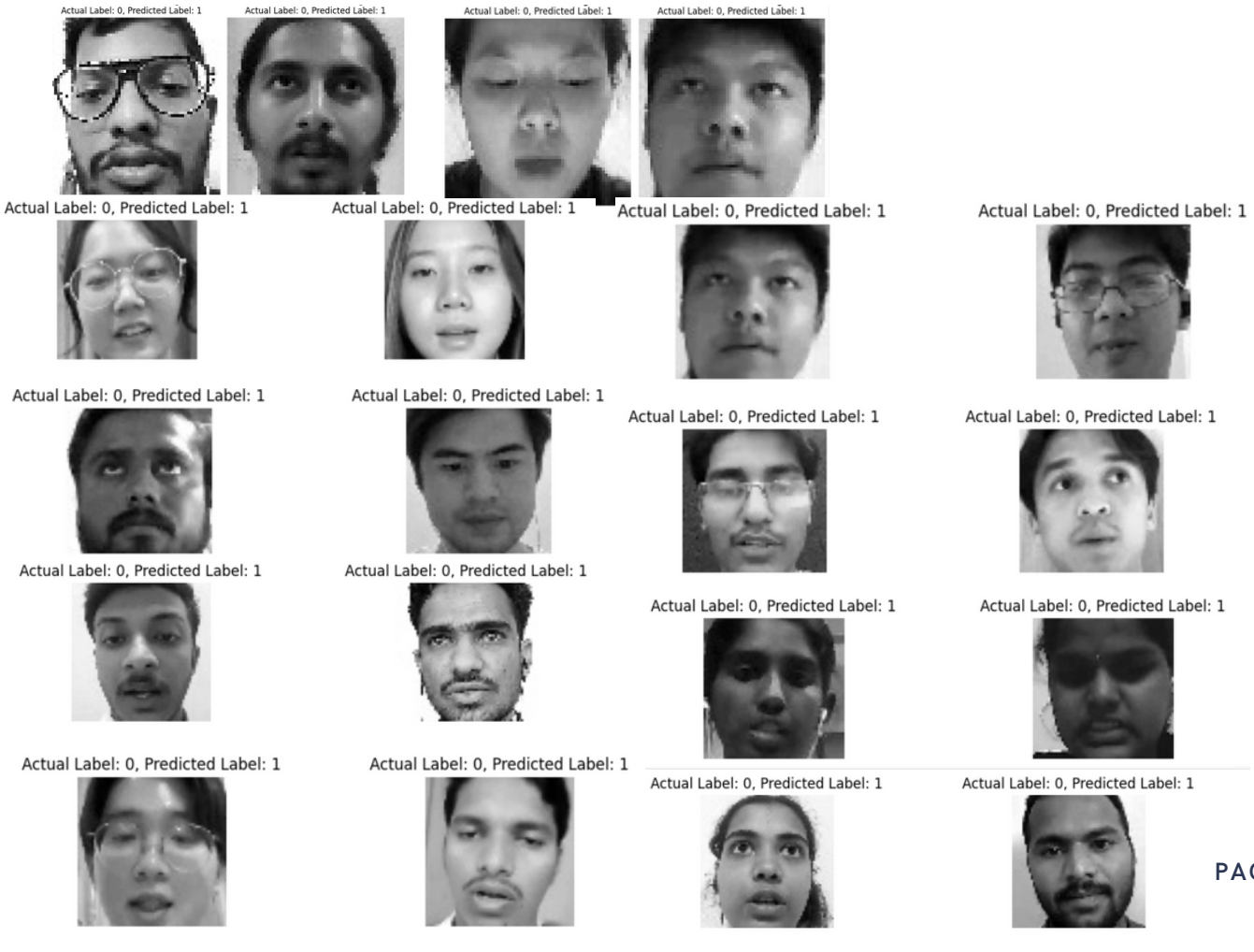
VISUALISING THE DECISIONS MADE BY THE MODEL

FALSE NEGATIVES



Most of the False negatives were due to wrongly detected ROIs by the Viola Jones Face detection Algorithm and the reason behind the wrong detection could be due to partial face in front of the camera, complex backgrounds with certain patterns etc. The algorithm requires the complete face to be in front of the camera for the face to br rightly identified

FALSE POSITIVES



VISUALISING THE DECISIONS MADE BY THE MODEL

TRUE NEGATIVES

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

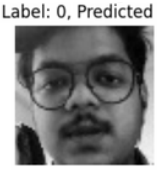
Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0



Actual Label: 0, Predicted Label: 0

TRUE POSITIVES

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

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Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 0, Predicted Label: 0

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

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Actual Label: 1, Predicted Label: 1

Actual Label: 1, Predicted Label: 1

PROMISING AREAS FOR FURTHER DEVELOPMENT

- Images could be resized to 128X128 px or 256x256 px and the model can be evaluated considering the loss of data when we resize the images to a standard of 64x64px for 2DPCA
- There is a increase in accuracy by 1% when you use ESRGAN upscaling.The benefits of this could be further improved if the images are of 128x128 size as we could lose less of the data provided by the ESRGAN upscaling when you resize it.
- Due to the lightweight nature of this model this shows potential of side deployment on the candidate's device rather than processing loads on the server
- With even more and diverse images to train on, the principle components extracted can accommodate a variation of faces thus improving the model accuracy.
- The principle components selected need to be looked into so they represent most of the population, making it suitable for all races
- Different models can be trained for specific geographic regions where there is a distinct variation in face features to increase the accuracy of recognising faces through principle components.
- The candidates can be made to sit in front of a simple, solid colour background, so the patterns wouldn't hinder the working of the face detection algorithm and detect a region other than the face.

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