INDIVIDUAL REPORT
TEAM 4
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Introduction

In the area of machine learning and deep learning, facial recognition technology is regarded as a key innovation, which enables a wide range of applications, from ensuring the security, to offering personalized customer experience. This report has been developed to present in detail various stages of the system development of facial recognition, covering the major difficulties, the used methods, and significant progress till the end. As a member of the COEN 240 Machine Learning course team 4, me and my team-mates Sai Revanth Sivaraju and Rajashekar Vennavelli, started this project in which we will study and gather the way of using machine learning algorithms to detect and determine facial images of our classmates.

Data Curation

The first step for the machine learning project is to make sure the data is clean and very well formatted. That lead to our process of data curation where we grouped each person images into each folder and named that particular folder that particular person's name. The mentioned framework was not only about accessing the required pictures for our training data but also it simplified the whole process of arranging the data clearly and in a simple way that the machine learning technology was provided with organized and structured data which led to learning from the data by the devices. We are achieving this way of organization using the MTCNN face detection algorithm. Where the face detection is done using the P-net where face is identified, then the Q-net where the non-facial regions are removed, then the R-net where the bounding box around the image is given based on the facial landmarks: eyes, nose, lips.

Data Augmentation

By acknowledging the restrictions brought about by a relatively small initial data set of 274 images, data augmentation techniques were included to increase the data set artificially to 1644 images. Augmentation techniques including operations such as changing brightness, applying a horizontal flip, rotating the images, and varying zoom levels, we created a wider bank of data points. This diversity allowed our models not only to learn how to differentiate features (including facial orientation, lighting, scale) but also to generalize them across various conditions, resulting in more robust facial recognition system.

Feature Extraction and Dimension Reduction

For feature extraction, we utilized two powerful neural network architectures: FaceNet and ResNet 50. Specific for the FaceNet is the production of embeddings that catch those features of a face that carry unique identity features. This in turn produce clusters of similar faces with those of the others that are closest in the embedding space. ResNet50 draws its superiority from the

deep style architecture and residual blocks, each of them taking care of certain very specific facial features, which serve as powerful attributes for face recognition tasks.
To study the dimension we used the principal component analysis concept (PCA) and also the linear discriminant analysis (LDA). PCA plays the role of dimension reduction so that the high degree of the data can be reduced to manageable scale without any significant loss information, therefore the model training ran faster and more efficiently. The LDA was employed to determine the necessary ratio of between the classes variance to within the classes variance of the features explaining the individual samples in the reduced dimensional space in a better way. The whole lay was made of PCA and LDA, which has permitted us to compute the models on data so the most discriminative features for facial recognition were emphasized.

Algorithms and Results

During the facial recognition project, we used four Machine Learning models which are KNN, Bayesian Classifier, SVM, and Decision Tree and examine their performance after different preprocessing and feature extraction techniques.
At first, the we fed the models with the Raw data(without any data augmentation) and got low accuracies of 58% for decision tree and SVM with 61% as notable models.
Next, we used MTCNN plus PCA, MTCNN plus LDA, MTCNN plus PCA and LDA, got improved results from the previous models with raw data. SVM got 86%, KNN with 76%, Bayesian classifier with 60% and decision tree with 63% for the MTCC plus PCA model. On the other hand, the use of MTCNN while combining it with PCA and LDA, and the MTCNN plus LDA resulted into the impressive result for SVM which for the range of 90.77% accuracy and KNN around 79%.
After trying all combinations it was FaceNet, MTCNN, and PCA featuring together which helped SVM and KNN to post a perfect 100% accuracy and rest around 94%. Thus, this setup, together with the created machine learning structure, was able to sustain the peak performance. Further implementing MTCNN, FaceNet, PCA plus LDA we get almost the same results with SVM and KNN with 100% and rest around 96%.
As a result of applying ResNet50 with PCA, the accuracy of our verification system appeared noteworthy with SVM with 93% and KNN with 86% and rest comparatively low. The results were almost similar with LDA added to the existing model. ResNet outputs very notable but slightly inferior to that of FaceNet algorithm, which fully confirms the latter's superiority in facial characteristics extraction.

Task Distribution and work done by me

First of all in our project on facial recognition our work began with joint endeavors in data curation and augmentation. Then we shared respective pipelines task based on our skills.
Revanth took the first half of the pipelines, and using algorithms KNN, Bayesian, SVM, and Decision Tree on were datasets processed with MTCNN, PCA, and LDA.
The main point of mine was to improve the pipelines 5 and 6, which I did by combining FaceNet with PCA and LDA for more effective feature extraction and better classification results. Performing the intricate task of matching FaceNet's deep learning with Dimensionality

Reduction techniques, I was able. Therefore, this allowed for accurate and effective model training. This period of the project made me investigate the specifics of feature extraction using neural networks and even boosts limits of our model's accuracy. Thus, we utilized ML pipelines to perform a feat that brought us to 100% accuracy with that of our SVM model, showcasing the impact of our methods.

Rajashekar has developed pipelines and has worked on 7 and 8 those used ResNet50, which employed PCA and LDA for extracting features and improving model training.

All of us are the equal owners of this project contributing 33.33% each making it a well effective team management and team contribution team.

Key learnings from this project

- It is very crucial to clean, curate, augment, preprocess the data for having a solid data foundation for the machine learning models.
- MTCNN helped effectively detect the faces in the initial stages for our data accumulation.
- FaceNet's deep learning algorithms created more effective facial embeddings, than ResNet50 in comparison, pointing out the need for selecting the right tools in the process of feature extraction.
- The PCA and LDA techniques turned out to be essential tools used to reduce data complexity and to take advantage of the class separation feature, hence classification became faster and simpler.
- Understanding of how the MTCNN, FaceNet, ResNet50 algorithms work. Need of Deep Learning
- Efficient project management was guided mainly through good distribution of tasks.

Key learnings from others project

The core contributions of other teams' experience were meant to detect several fundamental issues. The data augmentation which was identified as to be effective for eyeing up implementing more depth and greater generalization power by model was highlighted. Regardless of which pipelines have been adopted, the teams have proposed various innovative algorithms, aiming at the needs of different data features. This demonstrates that custom-made approaches would be required for specific data types. An increased focus was given on processing and standardization whose achievements were the accurate measurements equally required for model stability and accuracy since data scales have to be consistent. Recurrent the condition was the delicate balance between the model complexity and the performance on tasks with limited resources, a characteristic important for the practical applications. It is justifiable for a group to emphasize the importance of guiding through complexity, where deep learning is assigned for dealing with pattern recognition jobs, on the other hand; simple problems can be handled with traditional algorithms. The analyzing the current trends such as YOLO for real-time object detection has demonstrated how the area constantly keep on advancing. Tool selection was another point of concern for us during this process, and the right choice will tremendously affect the final result.