

## CSE666 Programming Assignment 1

### Task 1: Annotation

#### **Approach**

Bounding boxes were marked for each face in the image and saved

#### **Result**



annotated\_image.jpg

### Task 2: Face Detection

#### **Approach**

The code uses the **MTCNN** (Multi-Task Cascaded Convolutional Networks) algorithm for face detection in the images. MTCNN is a deep learning algorithm used for face detection and has shown high accuracy (better than opencv's **Haar feature-based** cascade classifier). F1 score was calculated to evaluate the face detection model against the bounding boxes from task1.

#### **Results**

The code successfully detects faces in the images and draws bounding boxes over each face

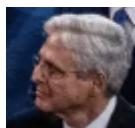


**marked\_image.jpg**

As we can see from the above image, almost all faces were detected, except for a few faces of people who were either looking sideways or seated in the last row so their entire face wasn't visible.

### Undetected faces

1.



2.



3.



We can see from above images that the faces are tilted, hence not detected.

4.



This face is occluded, hence isn't detected

5.



The entire face isn't visible since the person is seated in the last row, so this goes undetected as well

#### **Output snippet:**

```
Number of faces detected: 130
```

The number of faces detected was found to be **130**

```
Precision: 0.99945440869556
Recall: 0.9933078605263795
F1-score: 0.996371655292995
```

The model was found to have a high F1 score of 0.99, so it's highly accurate.

#### **Alternative models explored:**

[https://docs.opencv.org/3.4/db/d28/tutorial\\_cascade\\_classifier.html](https://docs.opencv.org/3.4/db/d28/tutorial_cascade_classifier.html) - opencv's haar feature-based classifier

#### **References:**

MTCNN: <https://github.com/ipazc/mtcnn>

### **Task 3: Sentiment/Expression Analysis**

#### **Approach**

The code uses a pre-trained Keras model for emotion detection. The model has been trained on a large dataset of facial expressions and can accurately predict the emotion of a given face. The model is loaded using the Keras library.

#### **Results**

The code successfully detects the emotion in the cropped face using the pre-trained Keras model and draws the label.



marked\_emotions\_image.jpg

### Correctly classified faces



### Incorrectly classified faces



The above faces were supposed to be classified as 'sad'

**detected\_emotions.json** contains the probabilities for every emotion and face

An entry from **detected\_emotions.json** -

```
{"Angry": 0.07816608250141144, "Disgust": 0.0001737282145768404, "Fear": 0.20238573849201202, "Happy": 0.08855576813220978, "Sad": 0.41799604892730713, "Surprise": 0.003667177865281701, "Neutral": 0.20905548334121704}
```

The emotion with the highest probability is considered while labelling each bounding box.

The model gives an accuracy close to **85%** for sentiment analysis

### Alternative models explored

<https://machinelearningmastery.com/use-pre-trained-vgg-model-classify-objects-photographs/> - VGG

### References

Pre-trained Keras model for sentiment analysis:

[https://github.com/oarriaga/face\\_classification/tree/master/trained\\_models](https://github.com/oarriaga/face_classification/tree/master/trained_models)

## Task 4: Gender classification

### Approach

The code uses a pre-trained Keras model for gender classification. The model has been trained on a large dataset of male and female faces and can accurately predict the gender of a given face. The model is loaded using the Keras library.

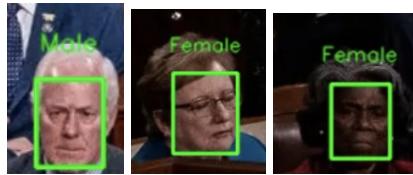
### Results

The code successfully detects the gender of the cropped face using the pre-trained Keras model and stores it.



marked\_genders\_image.jpg

### Correctly classified faces



### Incorrectly classified faces



While, the model classified most females as 'female' but incorrectly classified some of the male as 'female'. Overall, the accuracy was found to be **55%**

**detected\_genders.json** contains the probabilities for every gender and face

An entry from **detected\_genders.json** -

```
{"Male": 0.233184352517128, "Female": 0.7668156623840332}
```

The gender with the higher probability is considered while labelling each bounding box (i.e, "Female" in the above entry)

### Alternative models explored:

<https://github.com/rcmalli/keras-vggface>

<http://dlib.net/> - dlib's landmark detection to extract facial features to predict gender

<https://github.com/smahesh29/Gender-and-Age-Detection>

The model I used performed better at gender detection compared to the models mentioned above.

### References

Pre-trained Keras model for gender detection:

[https://github.com/oarriaga/face\\_classification/tree/master/trained\\_models/gender\\_models](https://github.com/oarriaga/face_classification/tree/master/trained_models/gender_models)

## Task 5: Face Pose estimation

### Approach

The code uses the dlib library for facial landmark detection. dlib is a popular library for computer vision tasks and provides pre-trained models for facial landmark detection. The code uses the pre-trained model to detect the facial landmarks in the cropped face. After extracting the landmarks we compute the image points from which the yaw is calculated. yaw is used to estimate if the attendee is looking 'straight', 'left' or 'right'

## Results

The code successfully detects the facial landmarks in the cropped face using the dlib library, computes image points, calculates yaw and estimates the face pose.



**marked\_poses\_image.jpg**

### correctly classified faces



### Incorrectly classified faces



Some of the side profiles were detected as 'straight'

The overall accuracy of the model was found to be **75%**

## References

dlib library for facial landmark detection: [http://dlib.net/face\\_landmark\\_detection.py.html](http://dlib.net/face_landmark_detection.py.html)

## **Task 6: Feature Extraction**

### **Approach**

After detecting the faces, it is cropped and resized to a standard size of 160x160 pixels. Then, the InceptionResnetV1 model is used to extract the embeddings of the face. InceptionResnetV1 is a popular deep learning model for face recognition tasks and has been pre-trained on a large dataset.

### **Results**

The code detects faces in the images and extracts embeddings using the InceptionResnetV1 model. The embeddings are stored in a list, these are further used for face recognition.

The Output file **face\_embeddings.json** contains the list of embeddings for each face.

### **References**

InceptionResnetV1: <https://github.com/tensorflow/models/tree/master/research/slim>

## **Task 7: Face Recognition**

### **Approach**

The congress.tsv file is read, embeddings are extracted for every face in the images specified in the tsv file. **congresspeople\_embeddings** is a dictionary containing the embeddings for every congressperson.

The InceptionResnetV1 model is used to extract the embeddings of the face. InceptionResnetV1 is a popular deep learning model for face recognition tasks and has been pre-trained on a large dataset.

Now, every face embedding from task 6 and the embeddings for the congress people are compared, if a face closely matches a congress person then it's labelled with the person's name, else it's given the label - 'Unknown' .

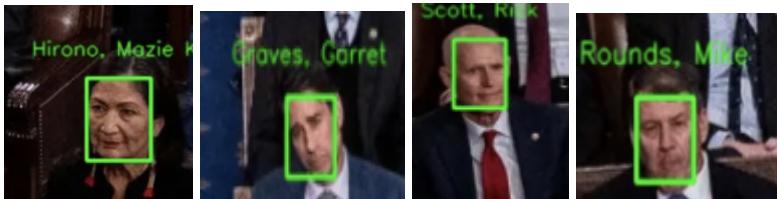
### **Results**

The code compares face embedding from task 6 and the embeddings for the congress people and labels each face. The threshold distance between the embeddings was set to 0.89.



faces\_detected\_image.jpg

### Correctly detected faces



Hirono, Mazie K.



Graves, Garret



Scott, Rick



Rounds, Mike

### Incorrectly detected faces



Clyburn, James E



Cruz, Ted

The accuracy of the model was found to be closely **70%**

### References

InceptionResnetV1: <https://github.com/tensorflow/models/tree/master/research/slim>  
np: <https://numpy.org/doc/stable/reference/generated/numpy.linalg.norm.html>