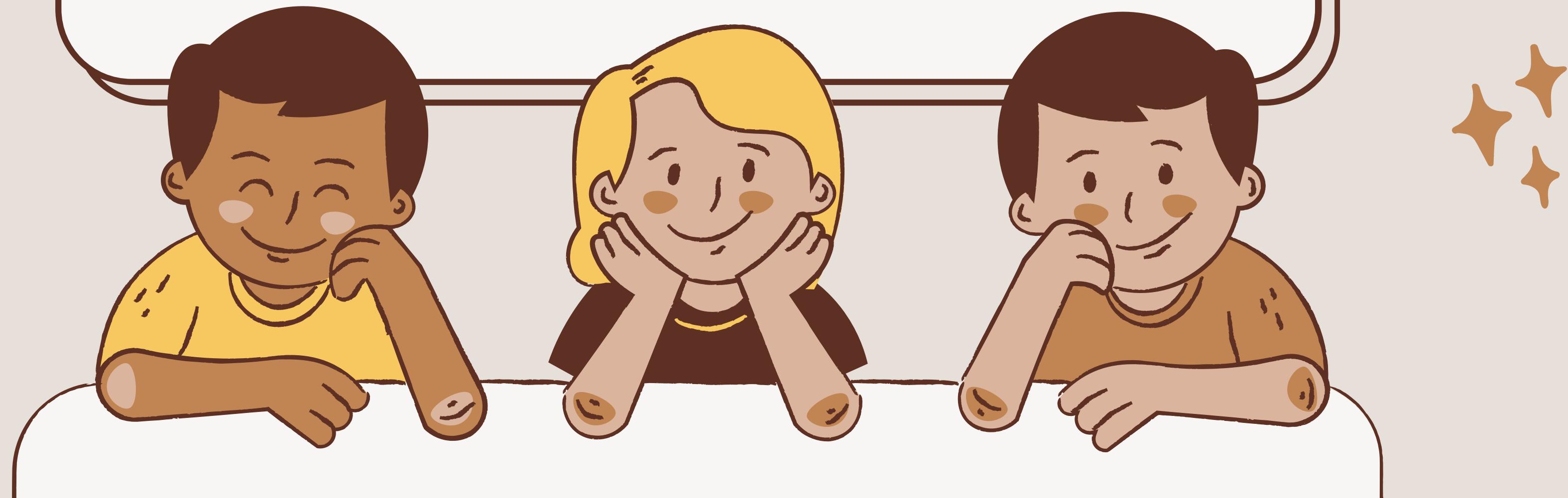


# DATING APP

TEAM 05

<https://github.com/lon5948/LAIAIAI>



# Outline

- introduction
- input/output
- evaluation metric
- four features
- future work

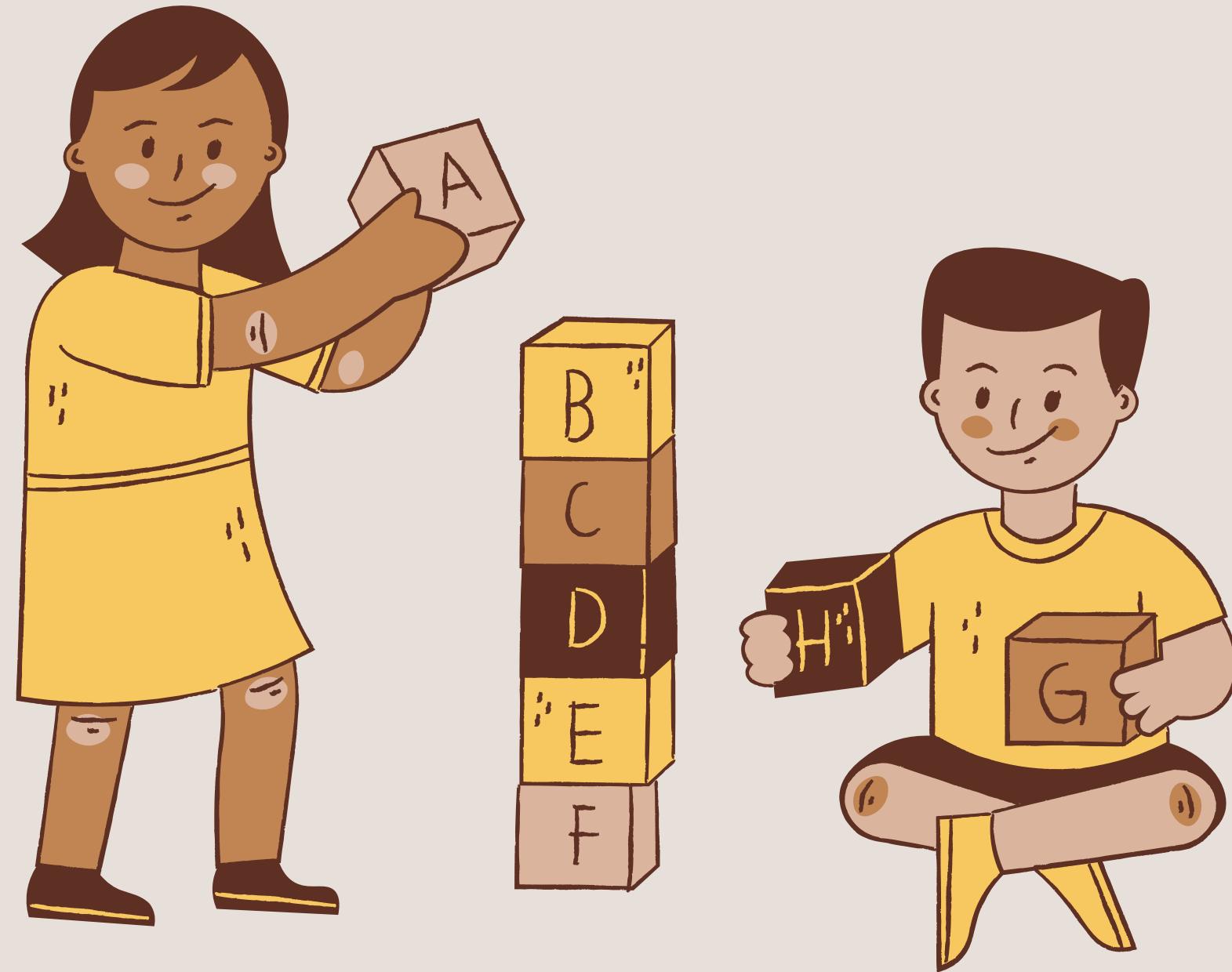


# INTRODUCTION

Due to pandemic, online dating has become the safest and most romantic way to meet a partner.

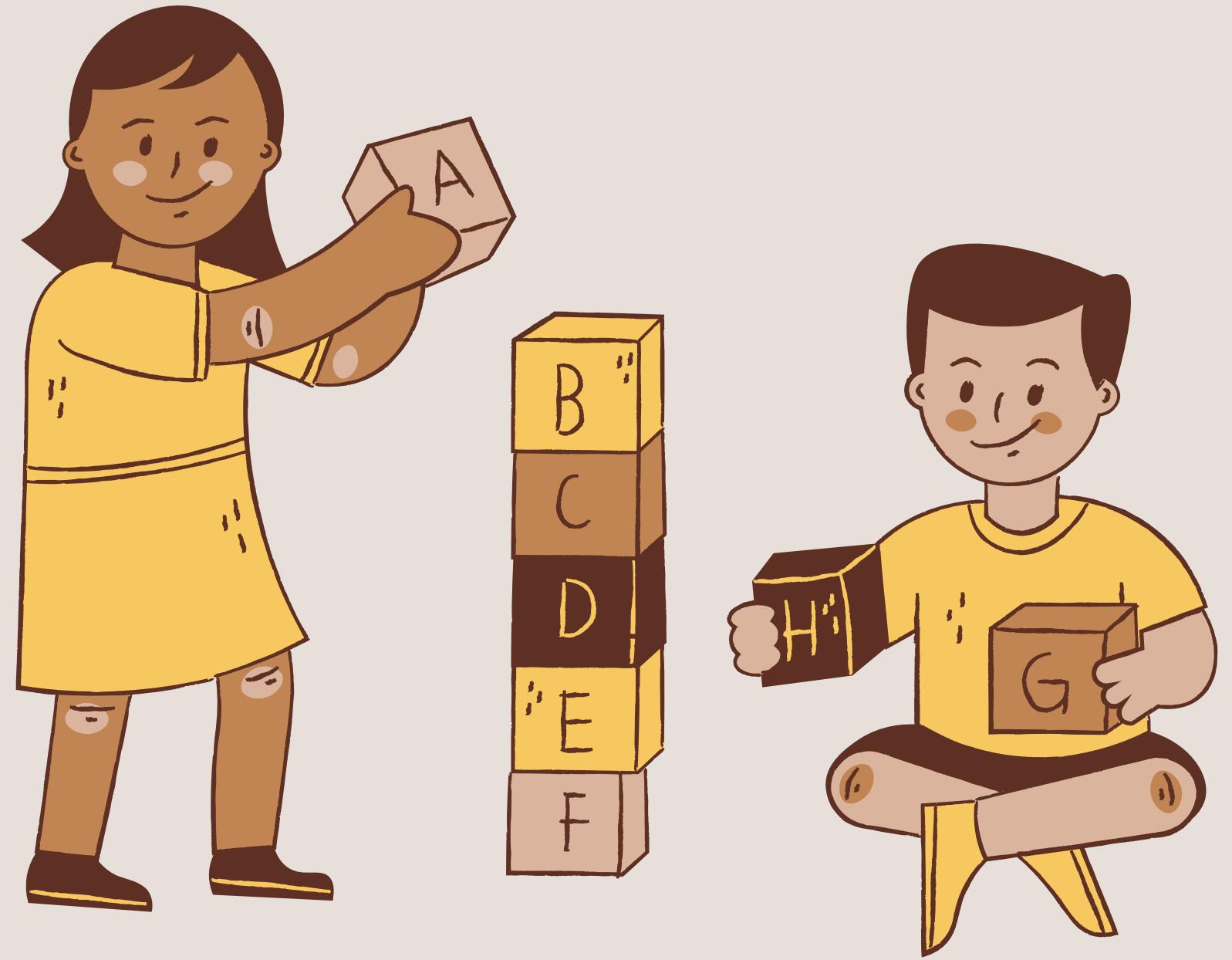
But the selection of photos is time consuming, thus, we'd like to introduce to you a Dating App that can classify human's faces and output photos with a face that you adore.





In this project, we will implement four classifiers on human faces, gender, face shape, skin color and eye color.

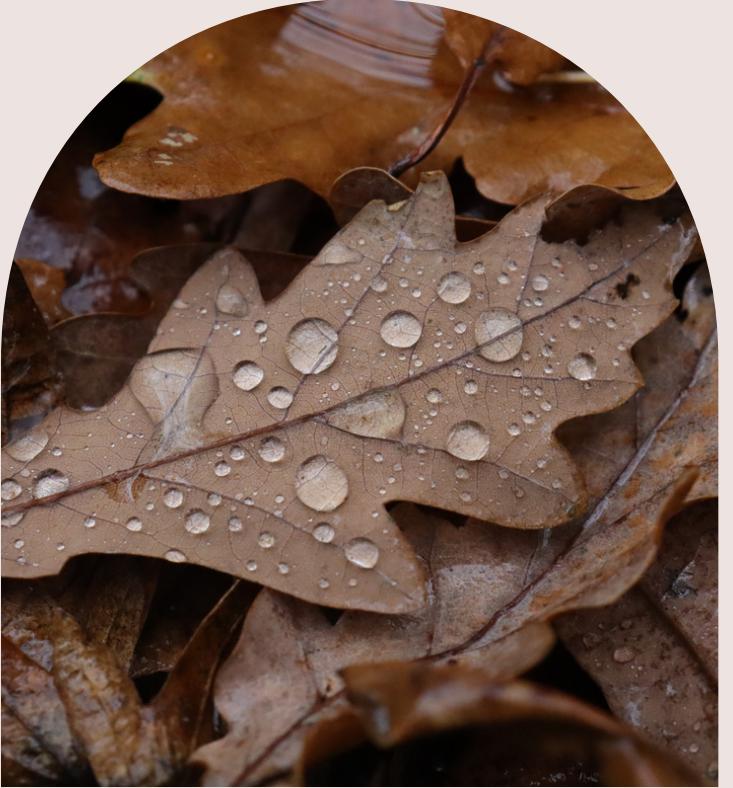
We will give an image of human face as input and output the four attributes that our system judges.



**Input:** image path

**Output:** string

- gender: Man / Woman
- face shape: diamond / oblong / oval / round / square / triangle
- race: Asian / Indian / Black / White / Middle eastern / Latino hispanic
- eye color: Black / Brown / Green / Blue

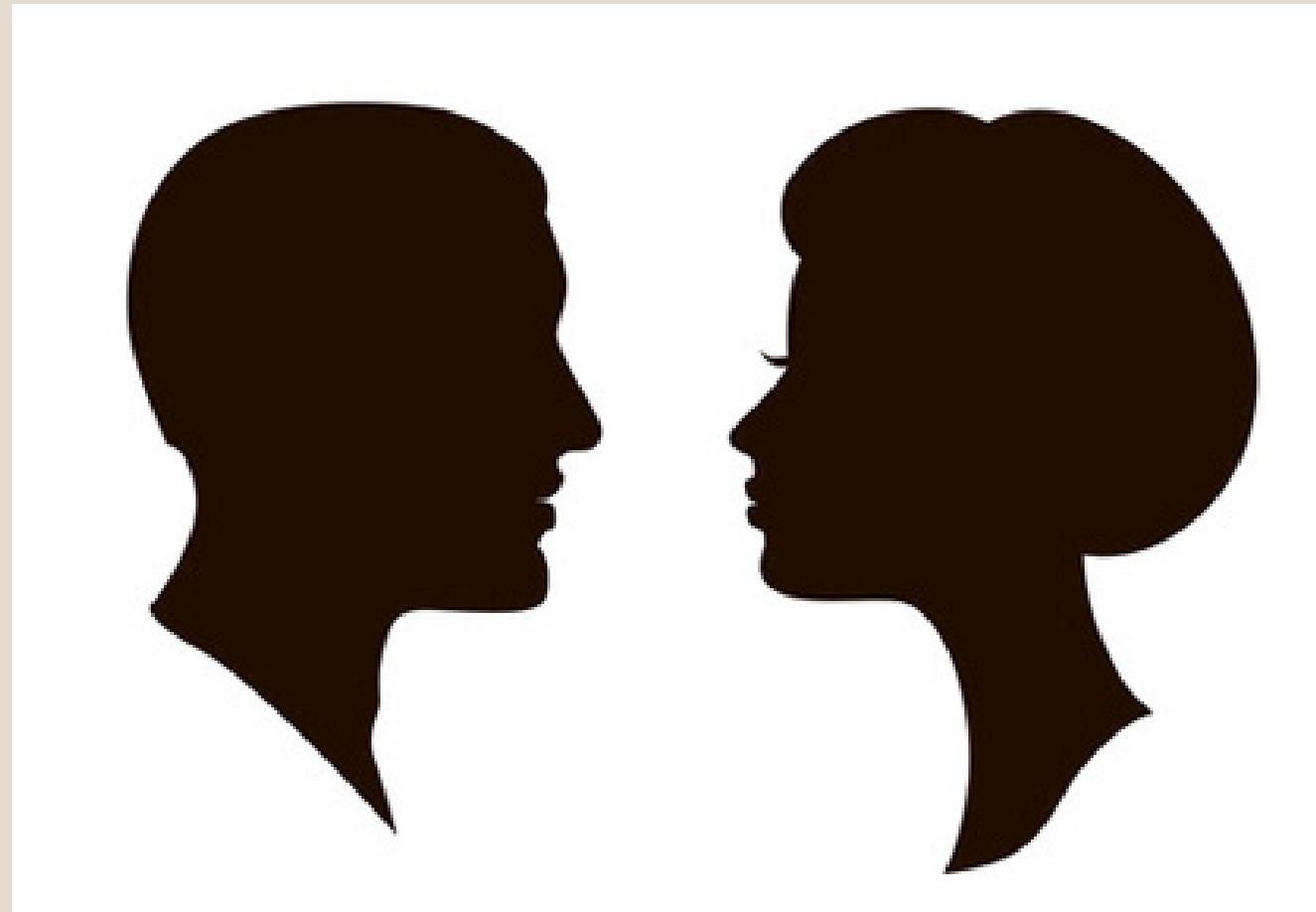


# Evaluation Metric

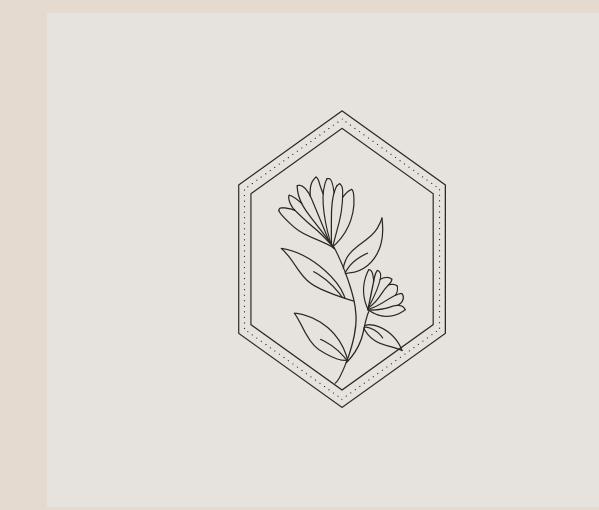
accuracy =  $\frac{1}{n} \sum_{i=1}^n f(x)$  where  $f(x) = \begin{cases} 1 & \text{if } \text{output} = \text{label} \\ 0 & \text{otherwise} \end{cases}$

# GENDER





# Model



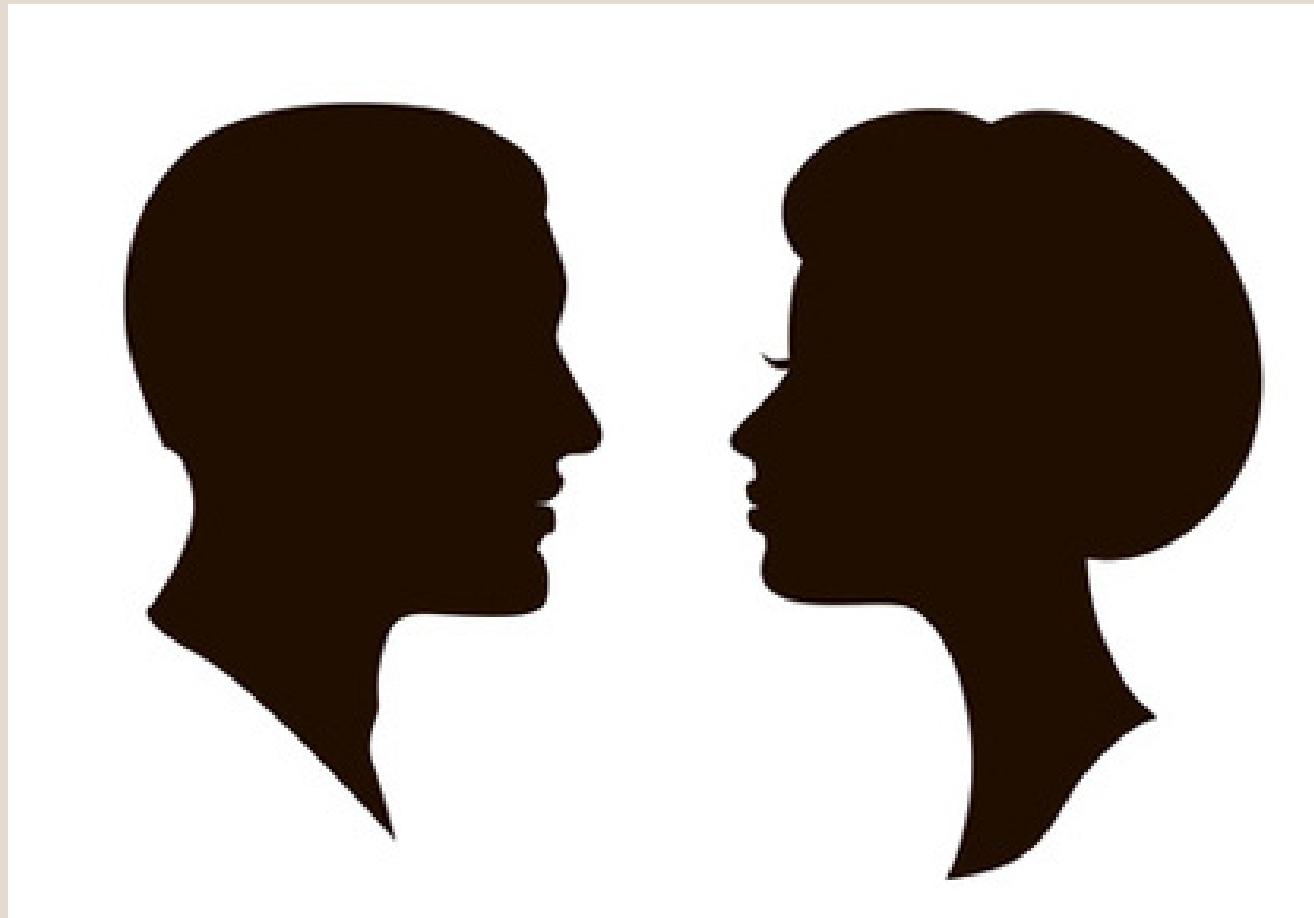
→  
**Baseline 1**  
**keras and cvlib**

**Baseline 2**  
**OpenCV and CNN**

**Model**  
**dlib and deepface**

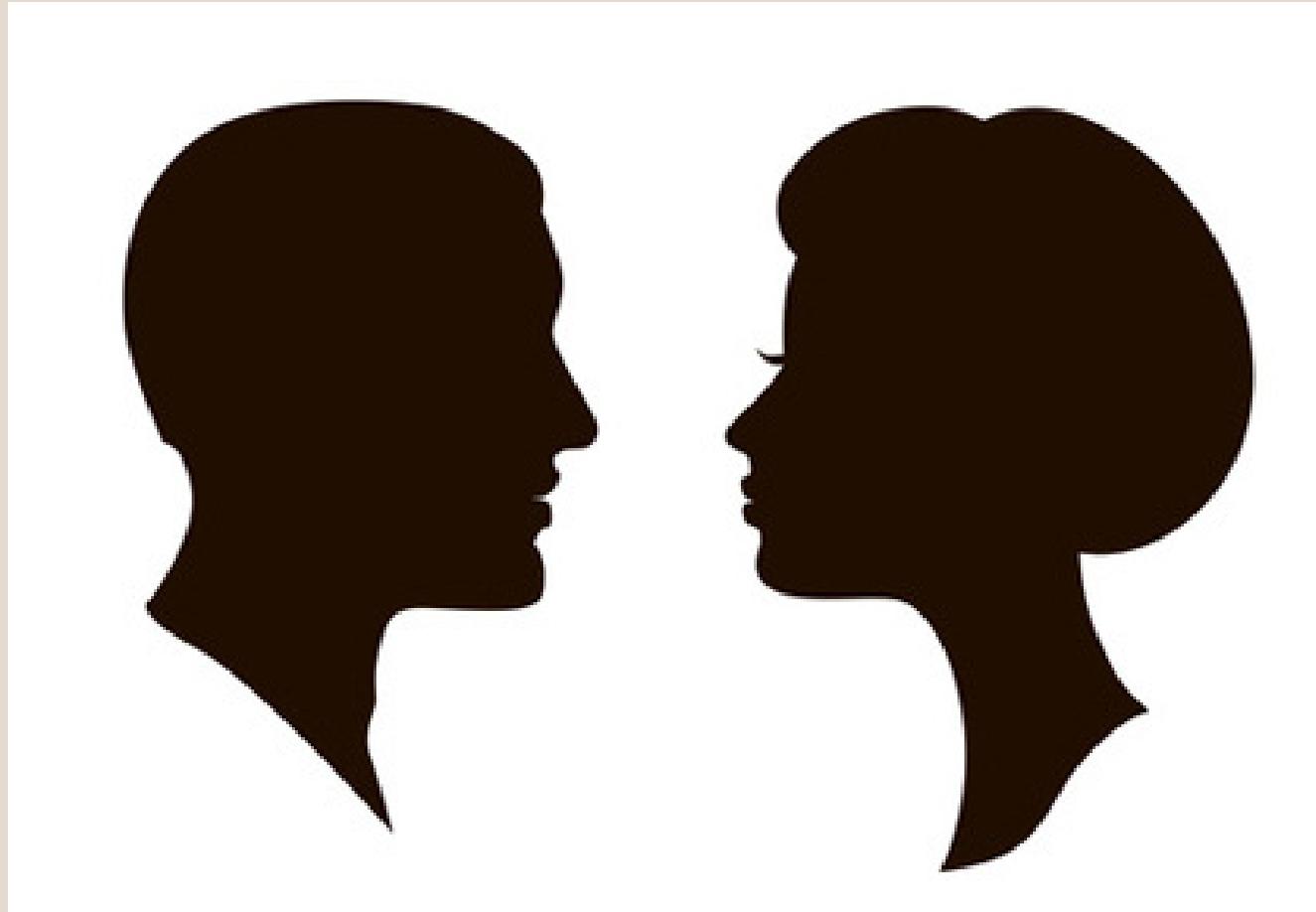


# Baseline 1



- import cvlib to use detect\_face()
- import Keras to built model
- convolution, batch normalization, MaxPooling, dropout
- batch normalizaton: gradient vanishing

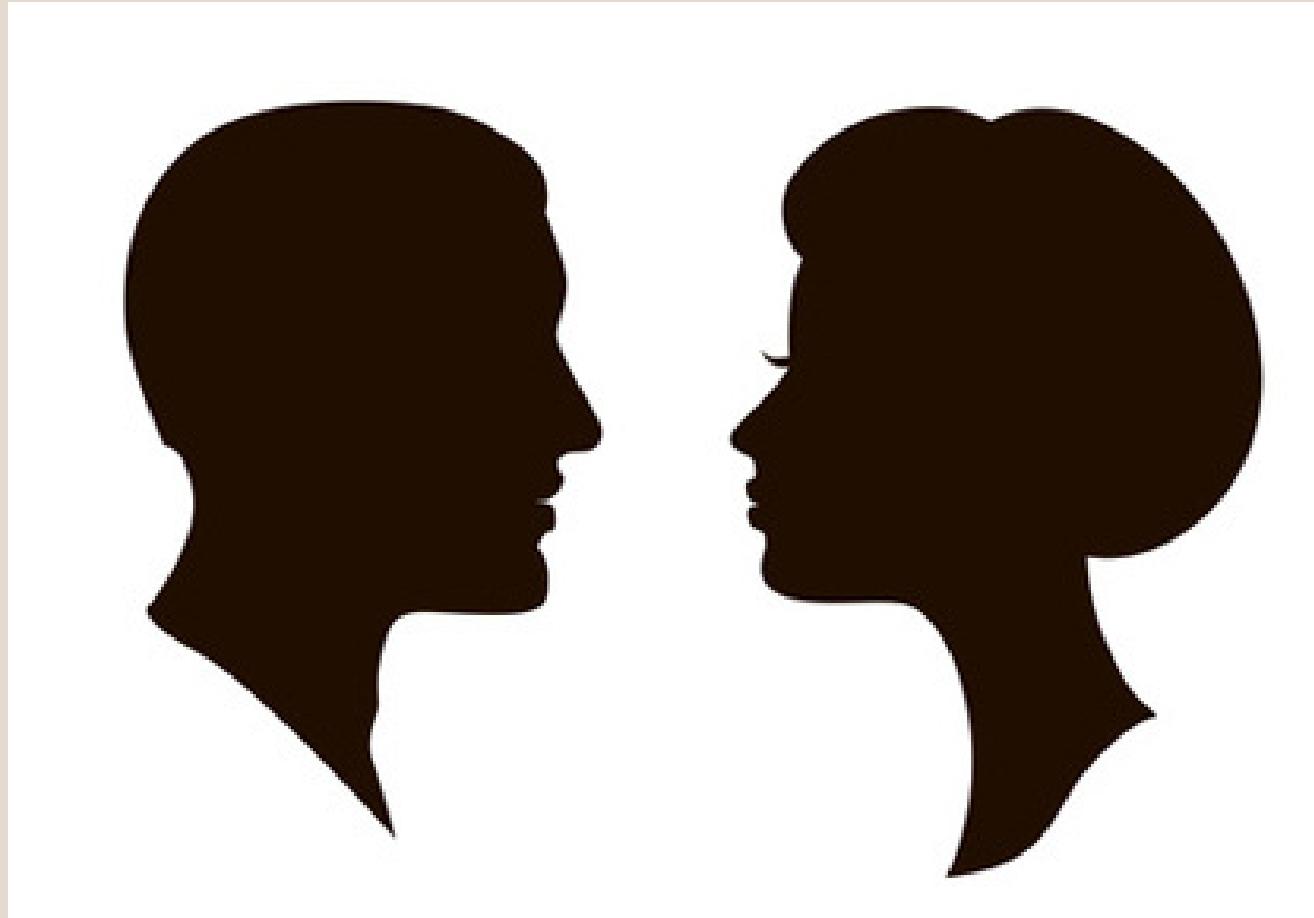
# Baseline 2



- import OpenCV and use haarcascade\_frontalface\_alt.xml
- import Keras to built model
- convolution, MaxPooling, dropout
- use dropout to avoid overfitting



# Model



- import face\_recognition to use  
face\_recognition.face\_locations()
- import deepface and VGGface
- Use pre\_trained model  
gender\_model\_weights.h5

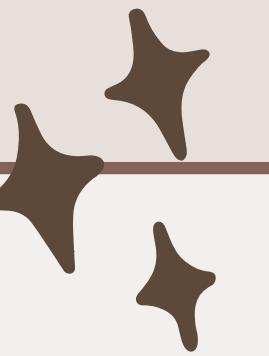
# Detail Implement of the Model

```
def transform_face_array2gender_face(self, face_array, grayscale=False, target_size = (224, 224)):  
    detected_face = face_array  
    if grayscale == True:  
        detected_face = cv2.cvtColor(detected_face, cv2.COLOR_BGR2GRAY)  
    detected_face = cv2.resize(detected_face, target_size)  
    #img_pixels = image.img_to_array(detected_face)  
    img_pixels = np.asarray(detected_face, 'f')  
    img_pixels = np.expand_dims(img_pixels, axis = 0)  
    #normalize input in [0, 1]  
    img_pixels /= 255  
    return img_pixels
```

# Detail Implementation of the Model

```
def predict_gender(self, face_image):
    image_preprocessing = self.transform_face_array2gender_face(face_image)
    gender_predictions = self.model.predict(image_preprocessing )[0,:]
    if np.argmax(gender_predictions) == 0:
        result_gender = "Woman"
    elif np.argmax(gender_predictions) == 1:
        result_gender = "Man"
    return result_gender

def loadModel(self):
    model = VGGFace.baseModel()
    #-----
    classes = 2
    base_model_output = Sequential()
    base_model_output = Convolution2D(classes, (1, 1), name='predictions')(model.layers[-4].output)
    base_model_output = Flatten()(base_model_output)
    base_model_output = Activation('softmax')(base_model_output)
    #-----
    gender_model = Model(inputs=model.input, outputs=base_model_output)
```



# ACCURACY WITH ONE PERSON PER PICTURE

	BASELINE 1	BASELINE 2	MODEL
MAN	0.85	0.92	0.98
WOMAN	0.75	0.81	0.82

# Testing dataset

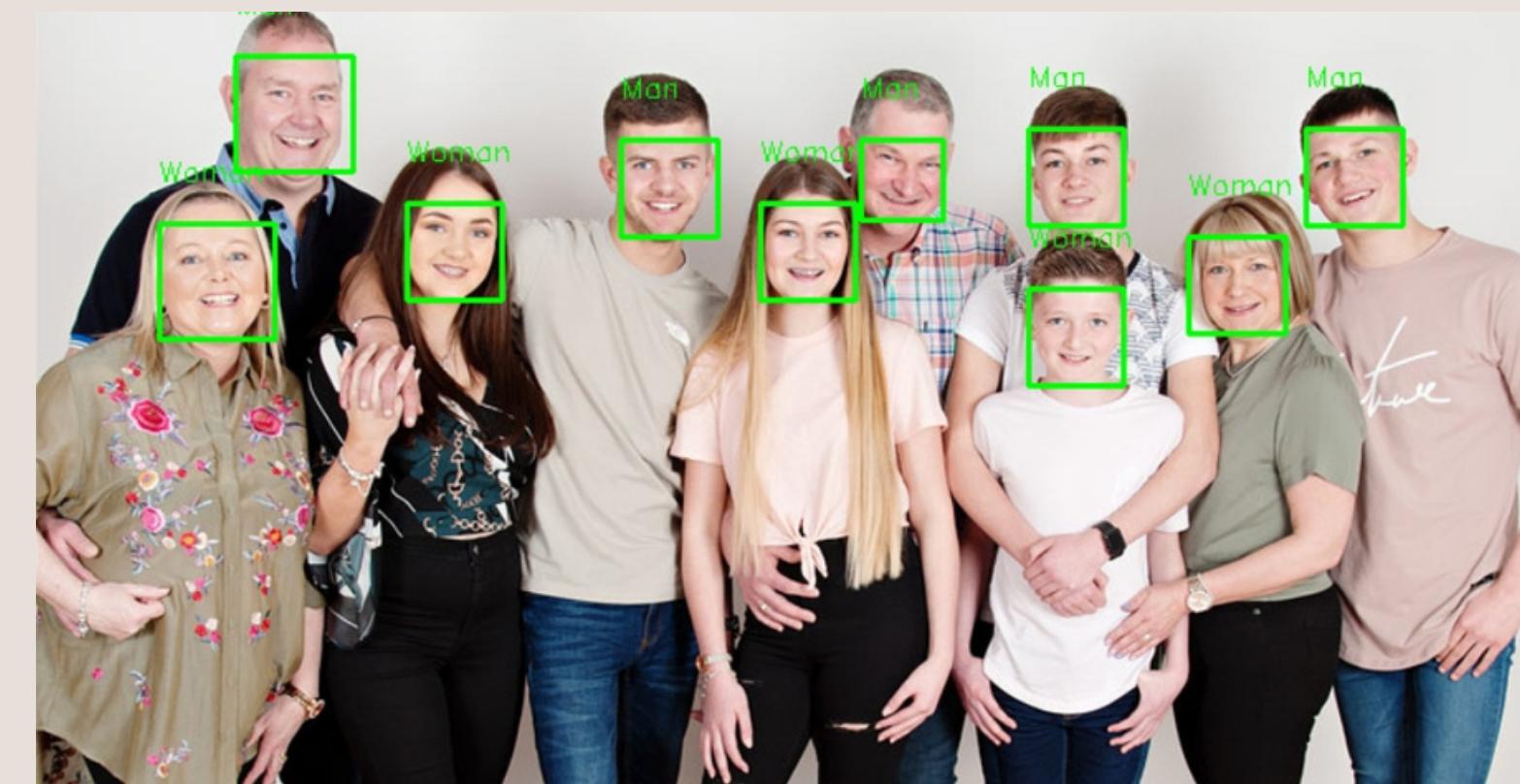


- US criminal photos, gender are labeled.  
<https://www.kaggle.com/datasets/davidjfischer/illinois-doc-labeled-faces-dataset>
- kaggle :<https://www.kaggle.com/datasets/ashwingupta3012/male-and-female-faces-dataset>

# MANY PEOPLE PER PICTURE



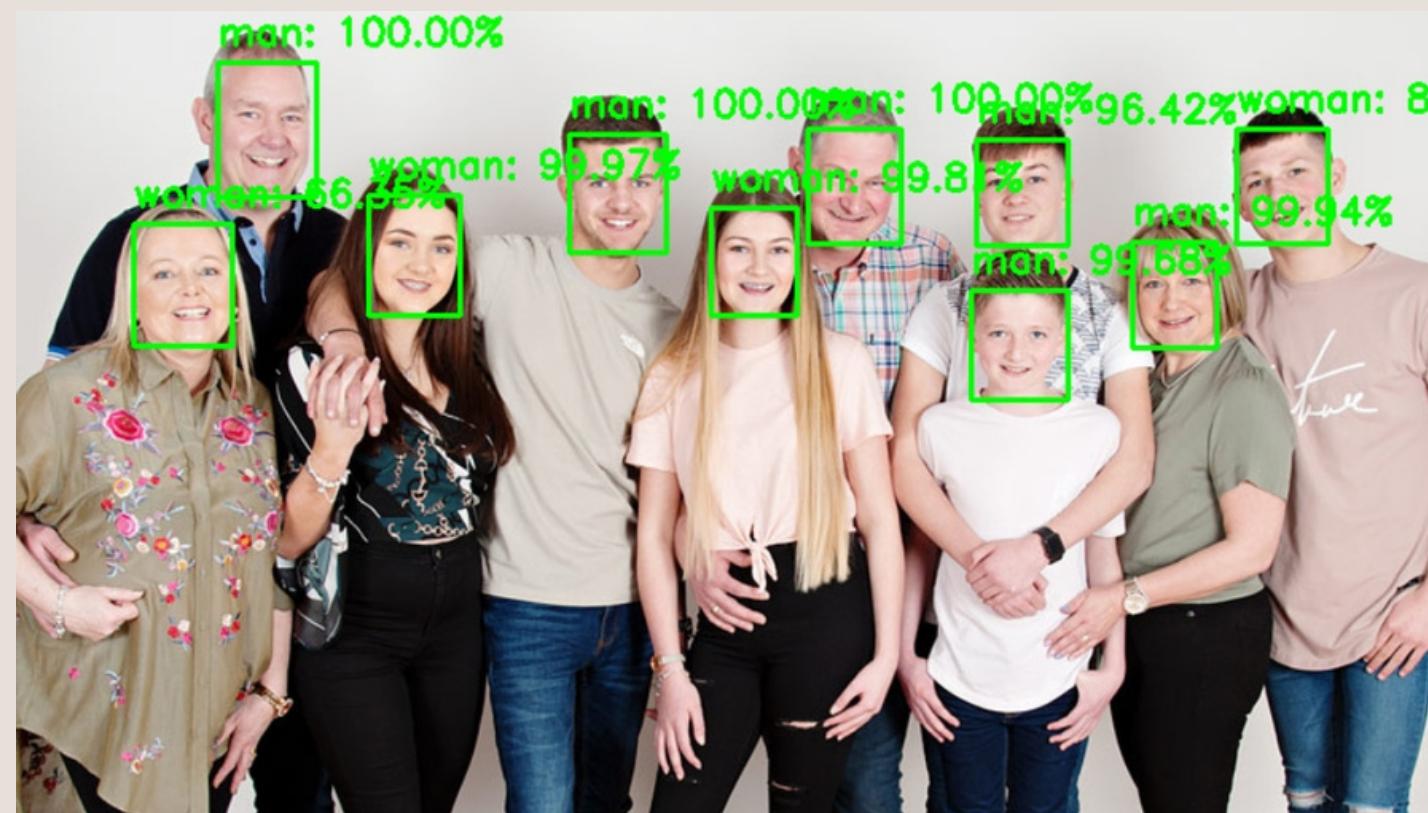
# MANY PEOPLE PER PICTURE



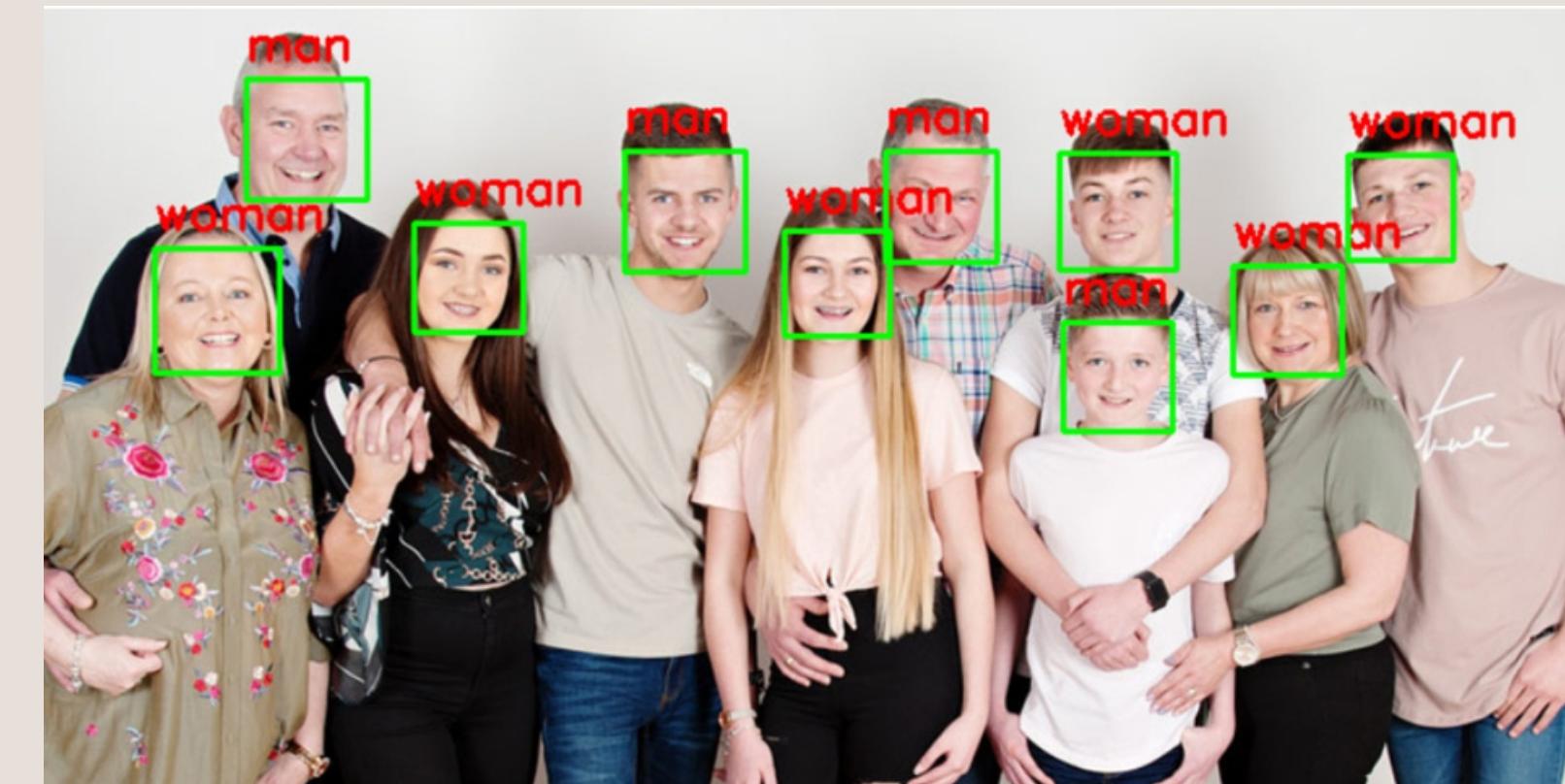
From Left to Right:  
W M W M W M M M W M

Model  
accuracy: 10/10

# MANY PEOPLE PER PICTURE



**Baseline 1**  
accuracy:8/10



**Baseline 2**  
accuracy:8/10

# UNCLEAR PHOTO

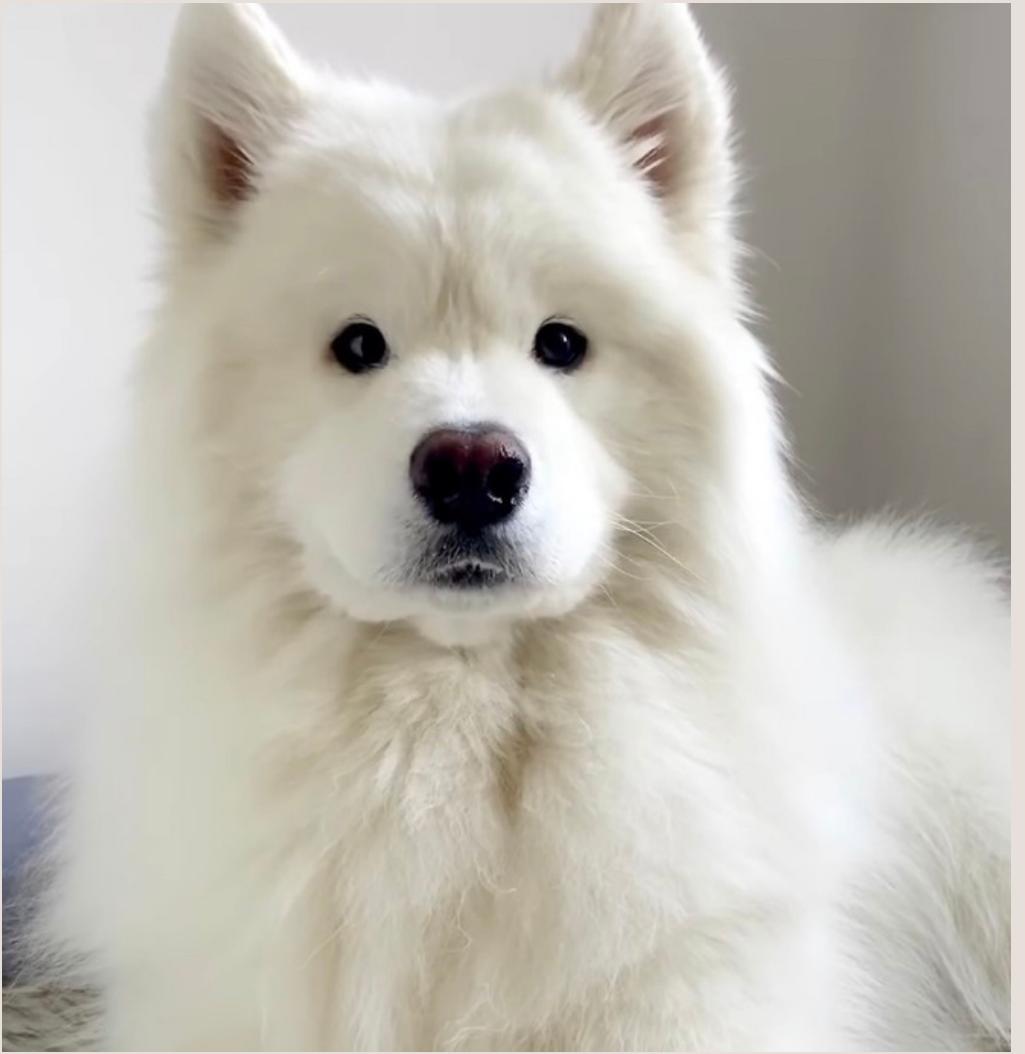


**Baseline 1: X**

**Baseline 2: X**

**Model: Woman**

# NOT A PERSON



**Baseline 1: Man**  
**Baseline 2: X**  
**Model: X**



**Baseline 1: Woman**  
**Baseline 2: X**  
**Model: X**

# REFERENCE



## BASELINE 1

<https://github.com/arunponnusamy/gender-detection-keras>

## BASELINE 2

<https://github.com/nman7/Facial-Gender-classification>

## MODEL

[https://github.com/juan-csv/Face\\_info](https://github.com/juan-csv/Face_info)  
[https://www.researchbank.ac.nz/bitstream/handle/10652/5395/MCOomp\\_2021\\_Changjin%20Wang%20%2B.pdf?sequence=1&isAllowed=y](https://www.researchbank.ac.nz/bitstream/handle/10652/5395/MCOomp_2021_Changjin%20Wang%20%2B.pdf?sequence=1&isAllowed=y)

# FACE SHAPE





# Related Work

- mood detection
- use distance/angles to determine result
- KNN algorithm

# Face Shape



Triangle



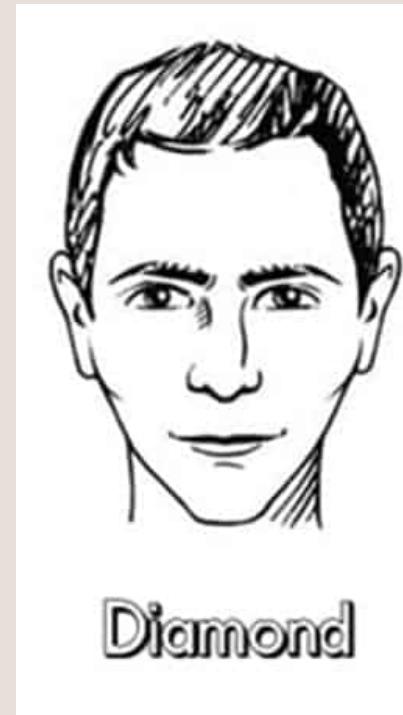
Oval



Round



Oblong



Diamond



Square





# Dataset

## kaggle

- no classification
- final test
- 100 pictures

## github

- diamond/oblong/oval/round/square/triangle
- 300 pictures each face shape
- calculate the accuracy





# Model



**Baseline 1**  
**face\_recognition**



**Baseline 2**  
**K Means Clustering**



**Model**  
**K Nearest Neighbor (KNN)**





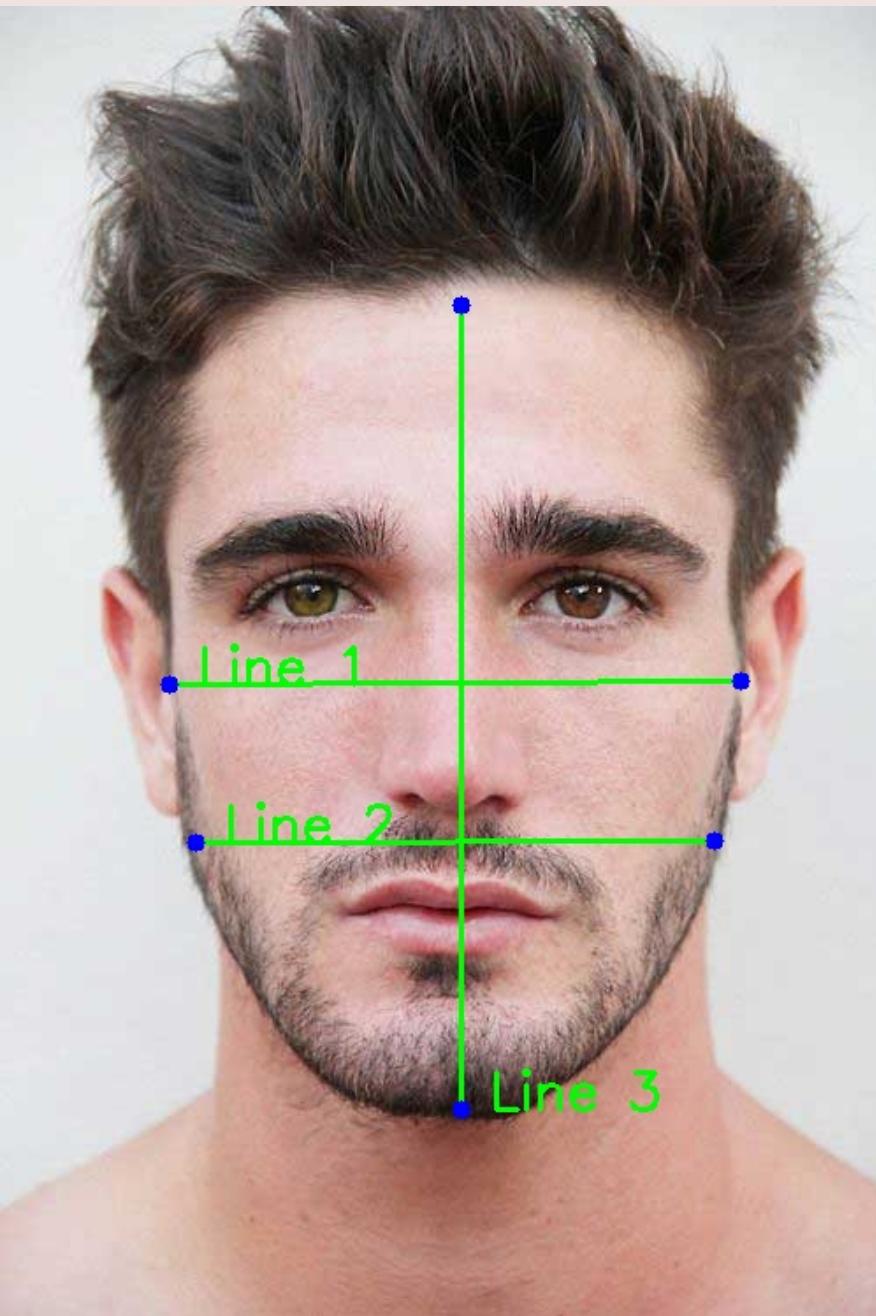
# Baseline 1

- import face\_recognition
- calculate the angle of jaw
- classification: three types



# Baseline 2

- K-means Clustering
- draw three lines
- calculate the angle of jaw
- classification: six types
- Unsupervised Learning

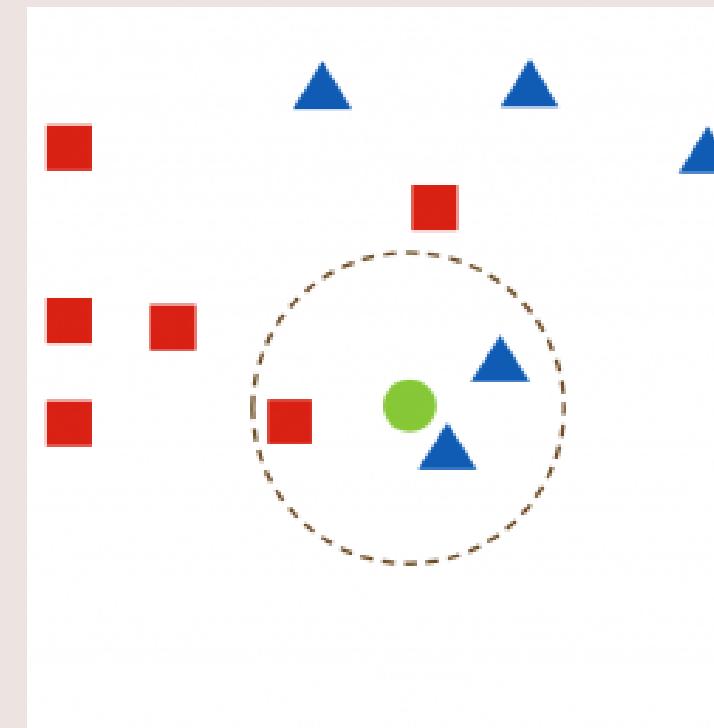


# K NEAREST NEIGHBORS



- determine k-value
- calculate the distance from yourself to every neughbors
- find k nearest neighbors
- join the group
- if can't join the group, do above steps again and again

# IS K-VALUE IMPORTANT?

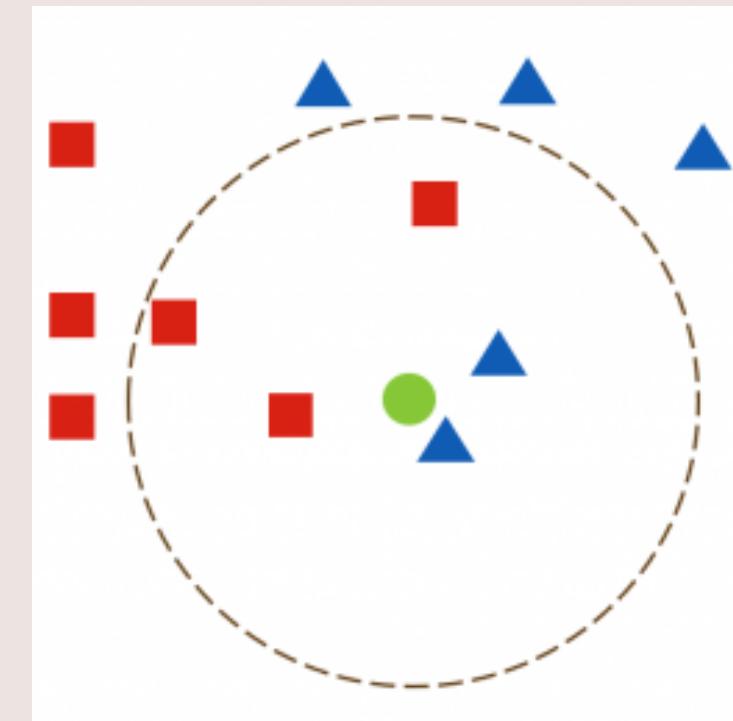


find 3 nearest neighbors,  
classification is blue triangle

$K = 3$

find 5 nearest neighbors,  
classification is red square

$K = 5$





# Training KNN

- data.pickle
- target.pickle
- scikit-learn (KNeighborsClassifier)
- KNN\_model.sav



→

# Face Detector

a pretrained face detecting classifier

# Landmark Detector

pretrained external algorithm



# Implementation

- `face_detector → rect`
- `landmark_detector → 68 points`
- Calculate Euclidean Distance
- KNN model
- get face shape

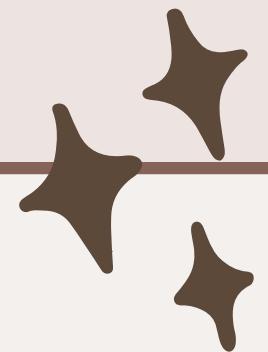


# Model



- KNN algorithm
- Supervised Learning
- faster
- classification: six types

# RESULT



	BASELINE 1	BASELINE 2	MODEL
SQUARE	47.3 %	37 %	93 %
OBLONG	X	26 %	91 %
OVAL	X	32 %	81 %
ROUND	2.51 %	39 %	88 %
DIAMOND	X	25 %	98 %
TRIANGLE	45 %	13 %	84 %

# ANALYSIS

- face shape in some images are ambiguous
- BASELINE 1 only three types but higher accuracy
- BASELINE 2 has more types but lower accuracy
- no matter which face shape, performance of KNN model is the best

# ERROR ANALYSIS

Square	93 %
oblong	91 %
OVAL	81 %
round	88 %
diamond	98 %
triangle	84 %

- some images misclassified by both models
  - Oval misclassified as Triangle
  - Mostly “Asian” Oval more mistaken as Round
  - Mostly “White” Round more mistaken as Oval
- six types has the highest performance



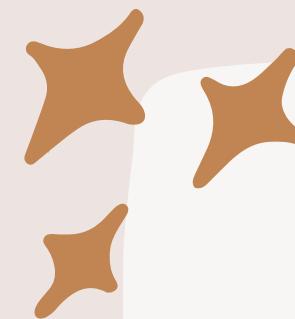
OVAL



# Fine-Tuning

- oval / triangle classification
- oval / round classification
- according to race, age, gender

# REFERENCE



## FACE RECOGNITION

[https://github.com/ageitgey/face\\_recognition](https://github.com/ageitgey/face_recognition)

## K MEANS ALGORITHM

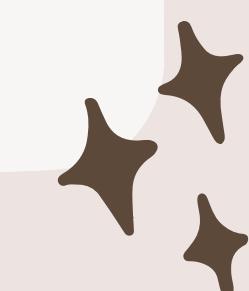
[https://github.com/BhagyaPerera/face-  
shape-recognition-system-](https://github.com/BhagyaPerera/face-shape-recognition-system-)

## KNN MODEL

[https://github.com/AakashBelide/gesture\\_  
control\\_and\\_mood\\_detection](https://github.com/AakashBelide/gesture_control_and_mood_detection)

## PAPER

[https://www.researchgate.net/publication/337  
386649\\_Face\\_shape\\_classification\\_using\\_Inception\\_v3](https://www.researchgate.net/publication/337386649_Face_shape_classification_using_Inception_v3)



# SKIN COLOR



# Dataset

1

YFCC-100M Flicker  
dataset

2

LFWA+ dataset

3

Illinois DOC labeled  
faces dataset  
(Kaggle)

# Baseline 1

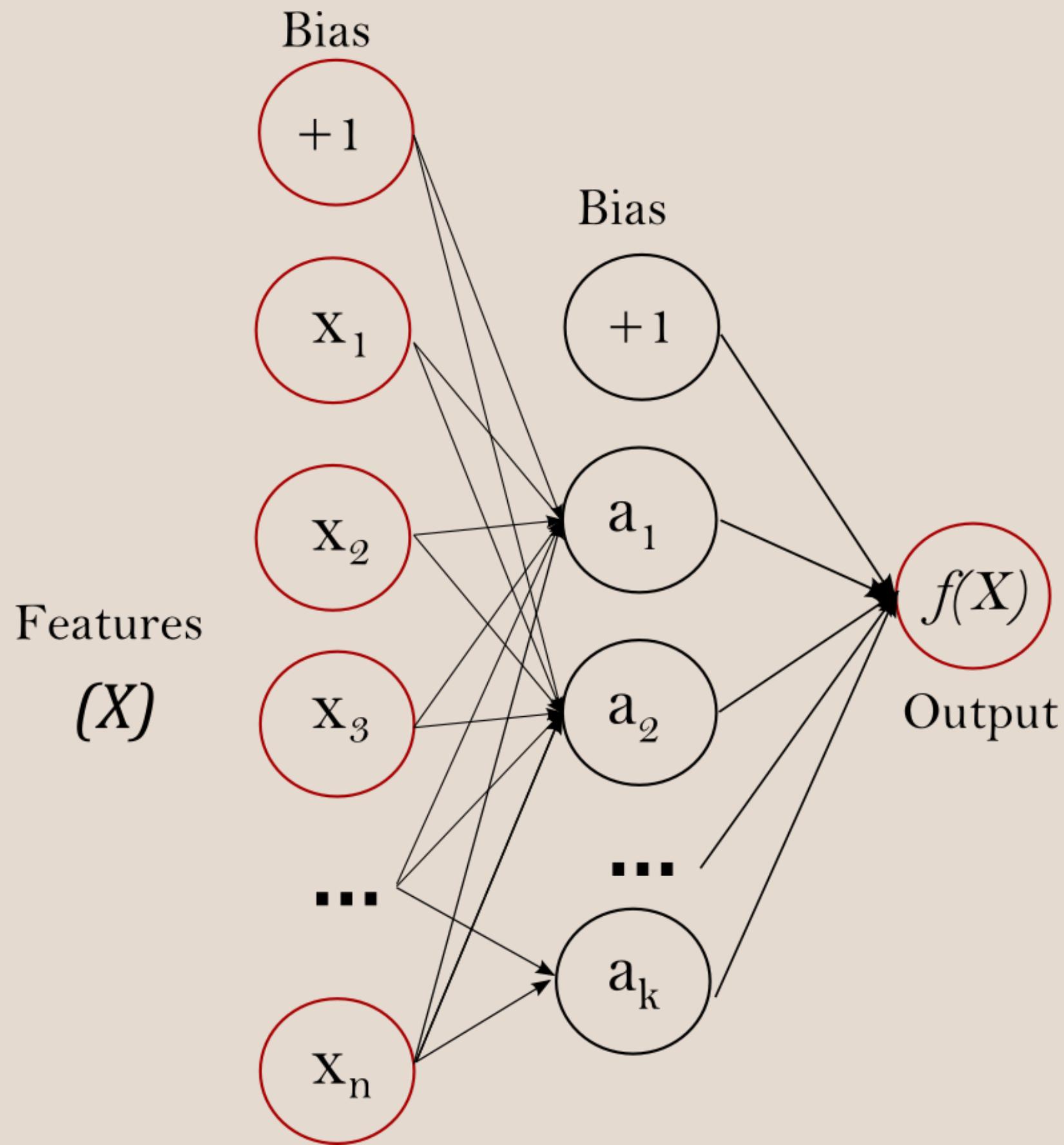
- White / Black / Asian / Indian
- dlib's CNN-based face detector
- Pretrained model ResNet-34
- FairFace: Face Attribute Dataset for  
Balanced Race, Gender, and Age for  
Bias Measurement and Mitigation

## Baseline 2

- Asian / Indian / Black / White / Middle eastern / Latino hispanic
- `face_recognition.face_locations()`
- keras' sequential model
- DeepFace: Closing the Gap to Human-Level Performance in Face Verification

# Model

- White, Black, Asian
- input : images
- output : string
- dlib's CNN-based face detector
- MLP classifier



“  
**MLP**  
**Multilayer Perceptron**

`solver = 'adam', hidden_layer_size = (128, 128),  
activation = 'relu', max_iter = 5000, tol = 1e-4`

# RESULT

	BASELINE 1	BASELINE 2	MODEL
ACCURACY	90.93195266272189%	89%	91.0207100591716%
LATENCY	5 min / 200 images	151 min / 6760 images	57 min / 6760 images

# ANALYSIS

- Baseline 2 detect face with HOG
- Baseline using ResNet

# MODEL RESULT

	N = 100	N = 200	N = 1000	N = 3000	N = 6760
ACCURACY	98%	95.5%	93%	92.36666%	91.0207100591716%

# ERROR ANALYSIS

- Number of labels :
  - model classifier < testing data

# REFERENCE



## BASELINE 1

<https://github.com/dchen236/FairFace>

## BASELINE2

[https://github.com/juan-csv/Face\\_info](https://github.com/juan-csv/Face_info)  
<https://github.com/serengil/deepface>

## MODEL

<https://github.com/wondonghyeon/face-classification>

# EYE COLOR





# Model



→  
**Baseline 1**  
**MTCNN detector**



**Baseline 2**  
**Pupil detection using**  
**DLIB**



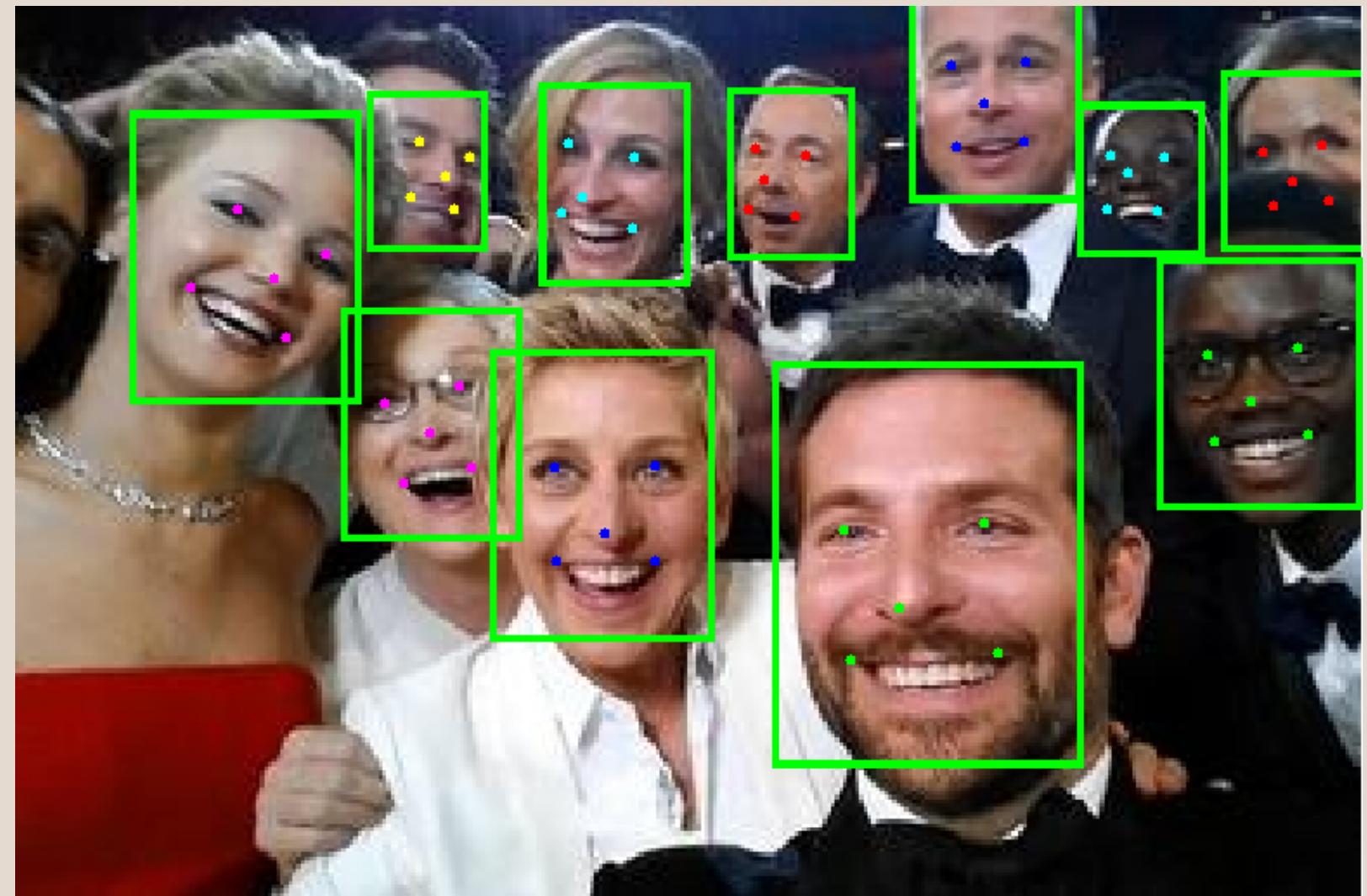
**Best model**  
**Iris extraction and detection**

# Baseline 1

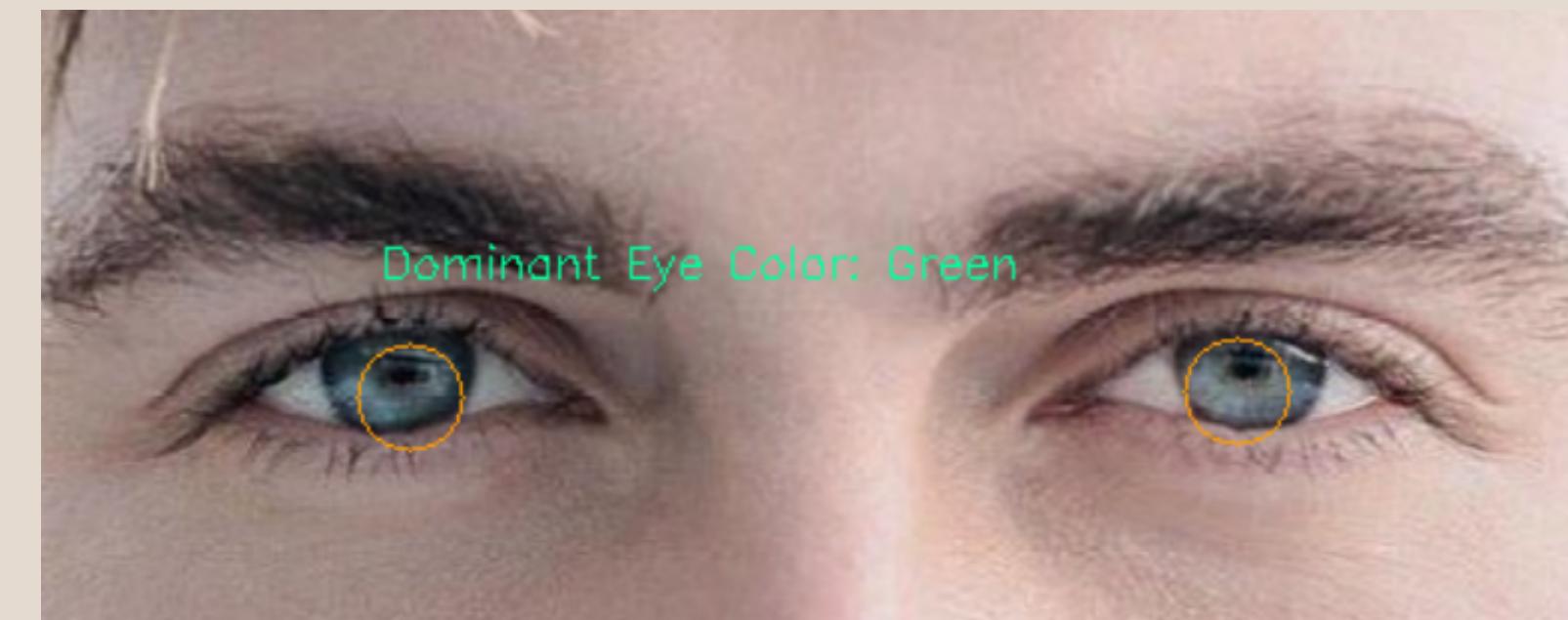
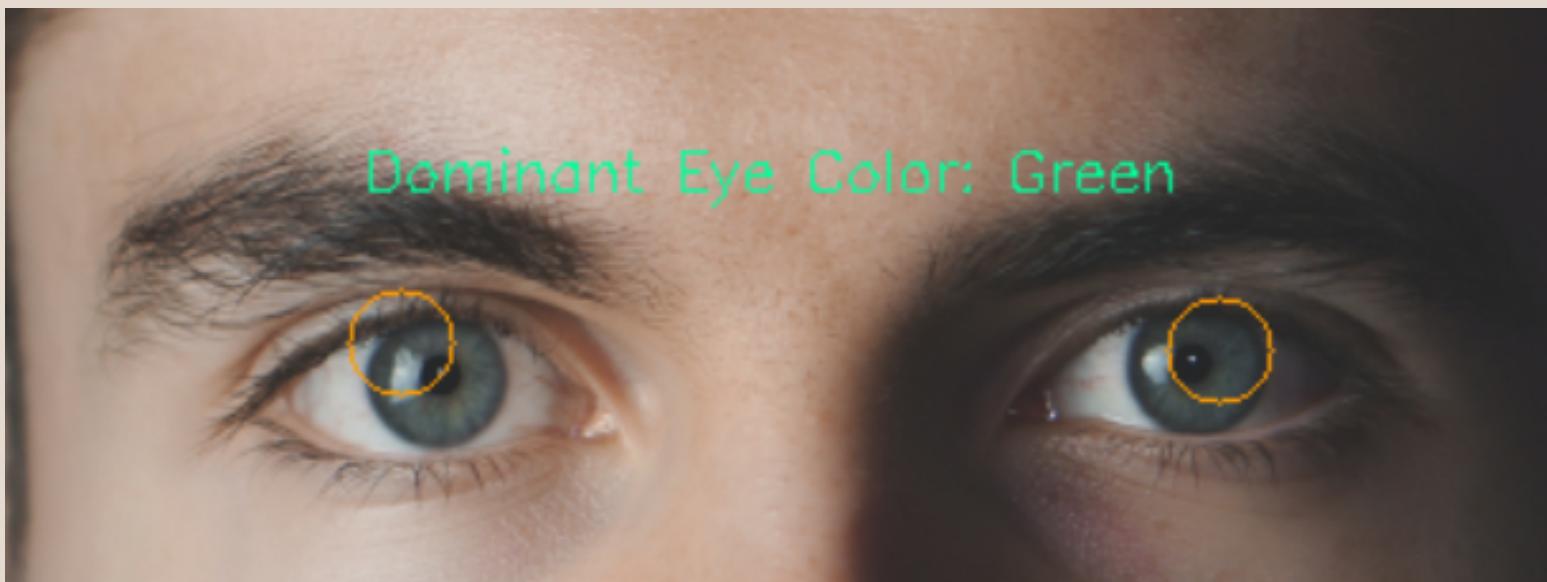
## MTCNN detector

→

- use mtcnn to catch 5 points.
- take left eye, right eye and eye's distance.
- approximate eye radius by  
 $\text{eye\_radius} = \text{eye\_distance}/15$
- circle eye area and detect HSV color.



# MTCNN detector - output

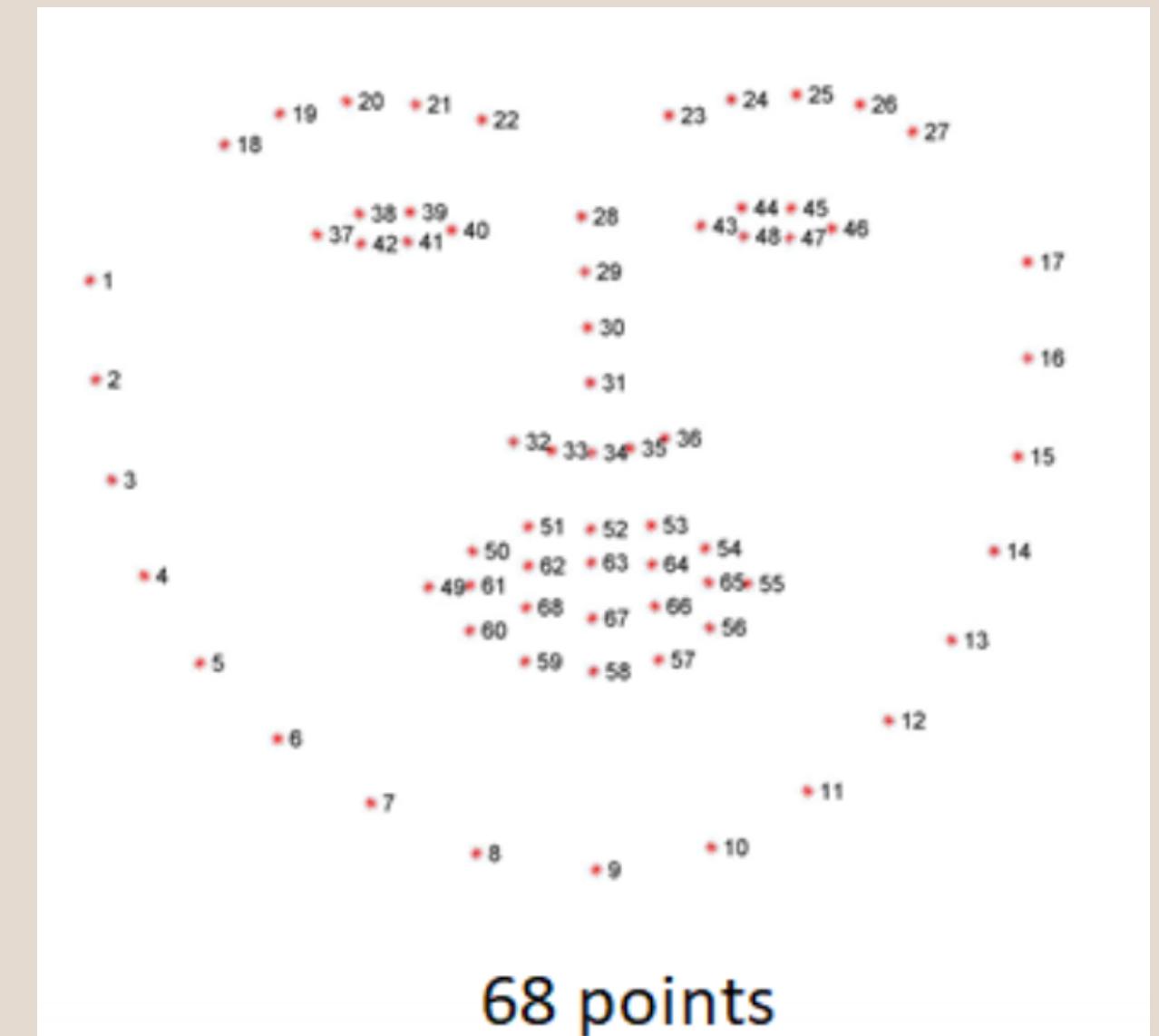


# Baseline 2

## Pupil detection using DLIB



- Using DLIB (68 points) to locate whole eye area
- considering eyes' common point: black pupil.
- catch Hough circle / the black part of eye as pupil point
- approximate iris area and detect HSV color.



# Detail Implementation of Pupil catching - I

```
def pixelReader(img,startHorizontal,startVertical,height):
    # list for satisfied pixels
    blackColour = []

    # for loops for traversing pixels
    for j in range(-int(height*1.5), 0):
        for i in range(startVertical- height,startVertical+int(height*1.5)):
            # setting lower bound for pixels, termination
            blackLowerRange = [80, 50, 50]
            pixel = startHorizontal + j
            colorCI = img[int(pixel), i]
            if ((colorCI[0] <= blackLowerRange[0] and colorCI[1] <= blackLowerRange[1]
                and colorCI[2] <= blackLowerRange[2])):
                blackColour.append([int(pixel), i])
    return blackColour
```



Judge if the pixel is black and collect the black area (as pupil point).

# Detail Implement of Pupil catching - 2

```
# after getting the eyes pixels applying cv2 method to detect circle pixels which we can do using houghcircles
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
circles = cv2.HoughCircles(gray, cv2.HOUGH_GRADIENT, dp = 1, minDist = 5,
| param1=250, param2=10, minRadius=1, maxRadius=-1)

# check if houghcircles has detect any circle or not
if circles is not None:
    circles = np.uint16(np.around(circles))
    for i in circles[0,:1]:
        pupilPoint = [int(eyeTopPointX[0])+ i[0],int(eyeBottomPointY[1]) + i[1]]
else:
    # if HoughCircles is unable to detect the circle than using eyes points to get pupil points
    a = 0
    for j,k in blackCoordinates:
        if a == int(len(blackCoordinates)/2):
            pupilPoint = [k,j]
            a += 1
return pupilPoint
```

1. Use hough circle function to detect circle.
2. Else, return the middle point of black area.

# Pupil detection - output



# Best model Iris extraction



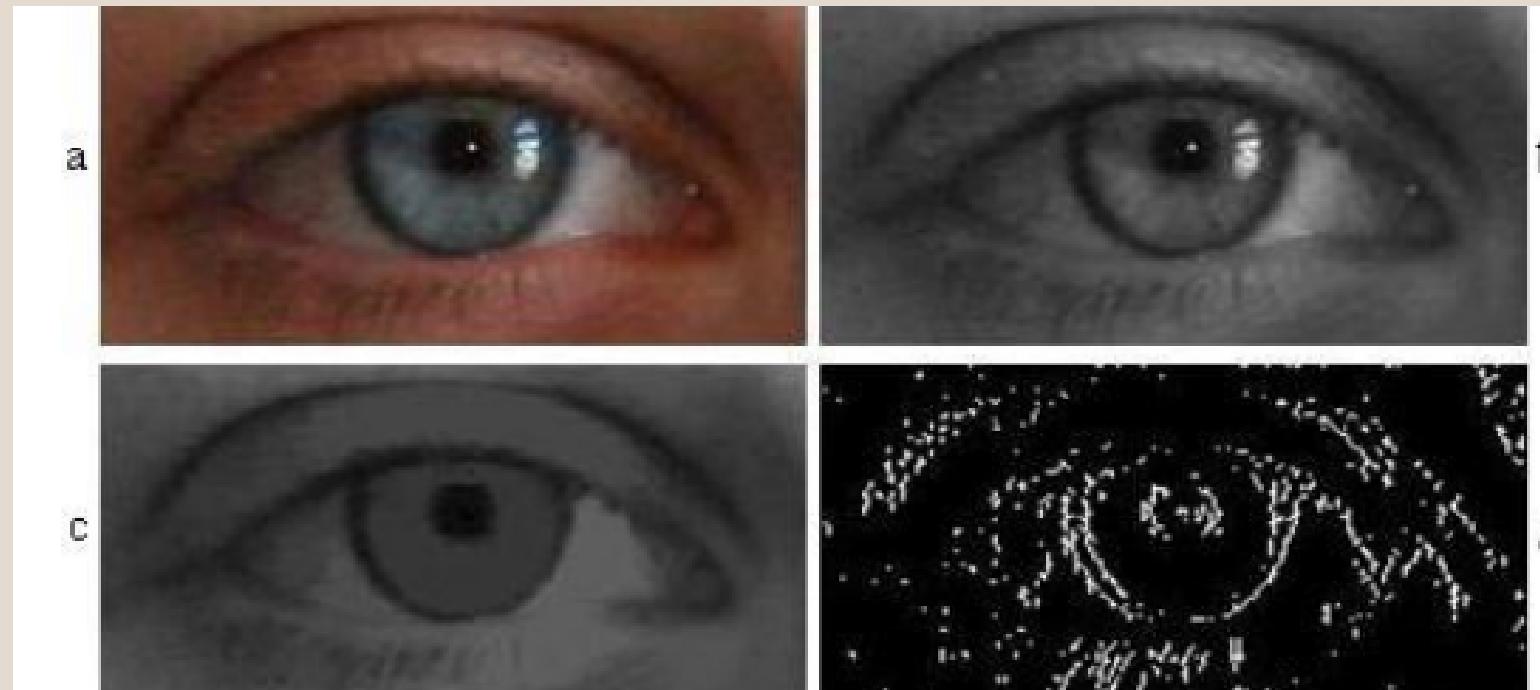
An automatic eye color detection algorithm

- Automatic iris extraction
- Manual region of interest (ROI) extraction (avoid pupil)
- HSV

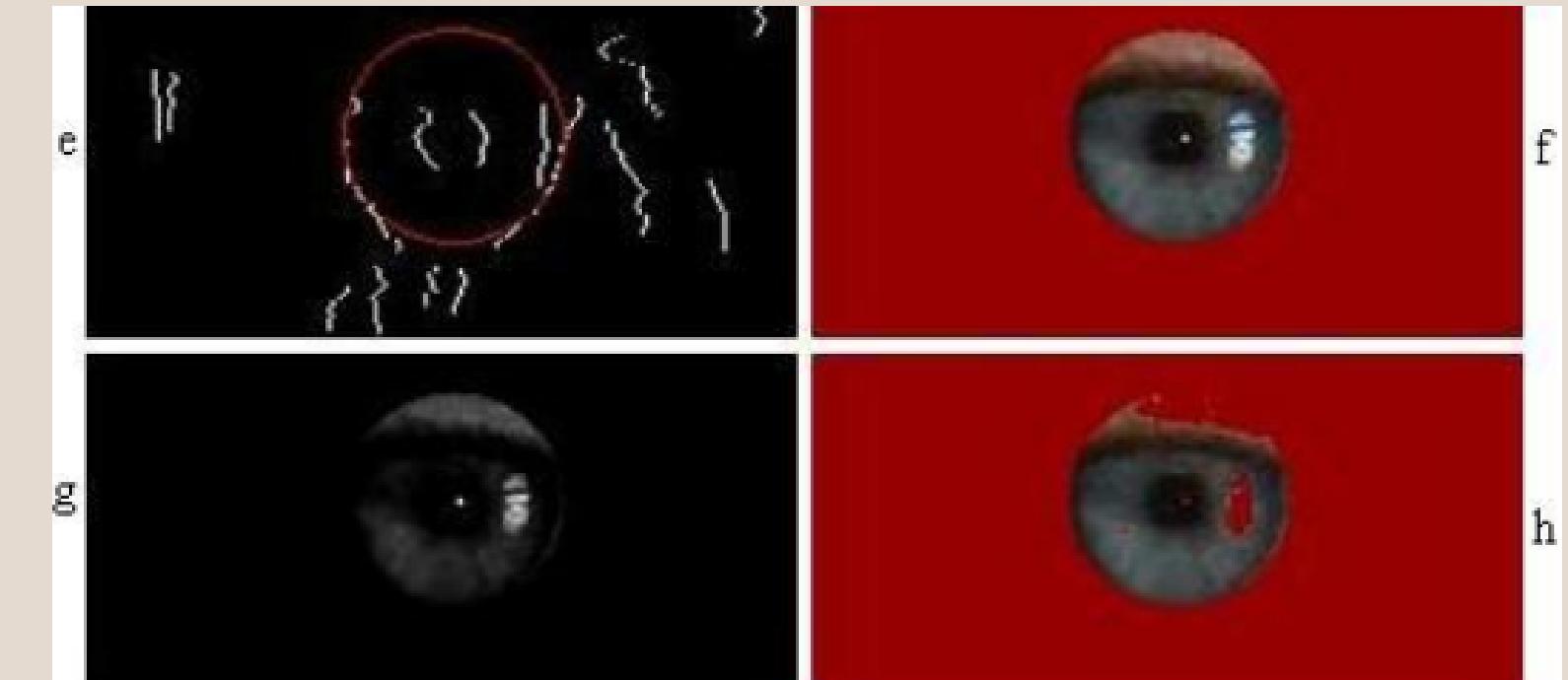
```
hsv_g = [95.62,44.44,28.23]
hsv_b1 = [205.06,40,53.72]
hsv_br = [27.18,78.05,32.15]
hsv_blk = [0.0,14.28,2.74]
distances = [hsvDist(colour,hsv_br) , hsvDist(colour ,hsv_b1), hsvDist(colour ,hsv_g ) , hsvDist(colour ,hsv_blk )]
majorColorIndex = np.argmin(distances)
```

reference: On the Reliability of Eye Color Classification as a Soft Biometrics Trait

# Automatic iris extraction



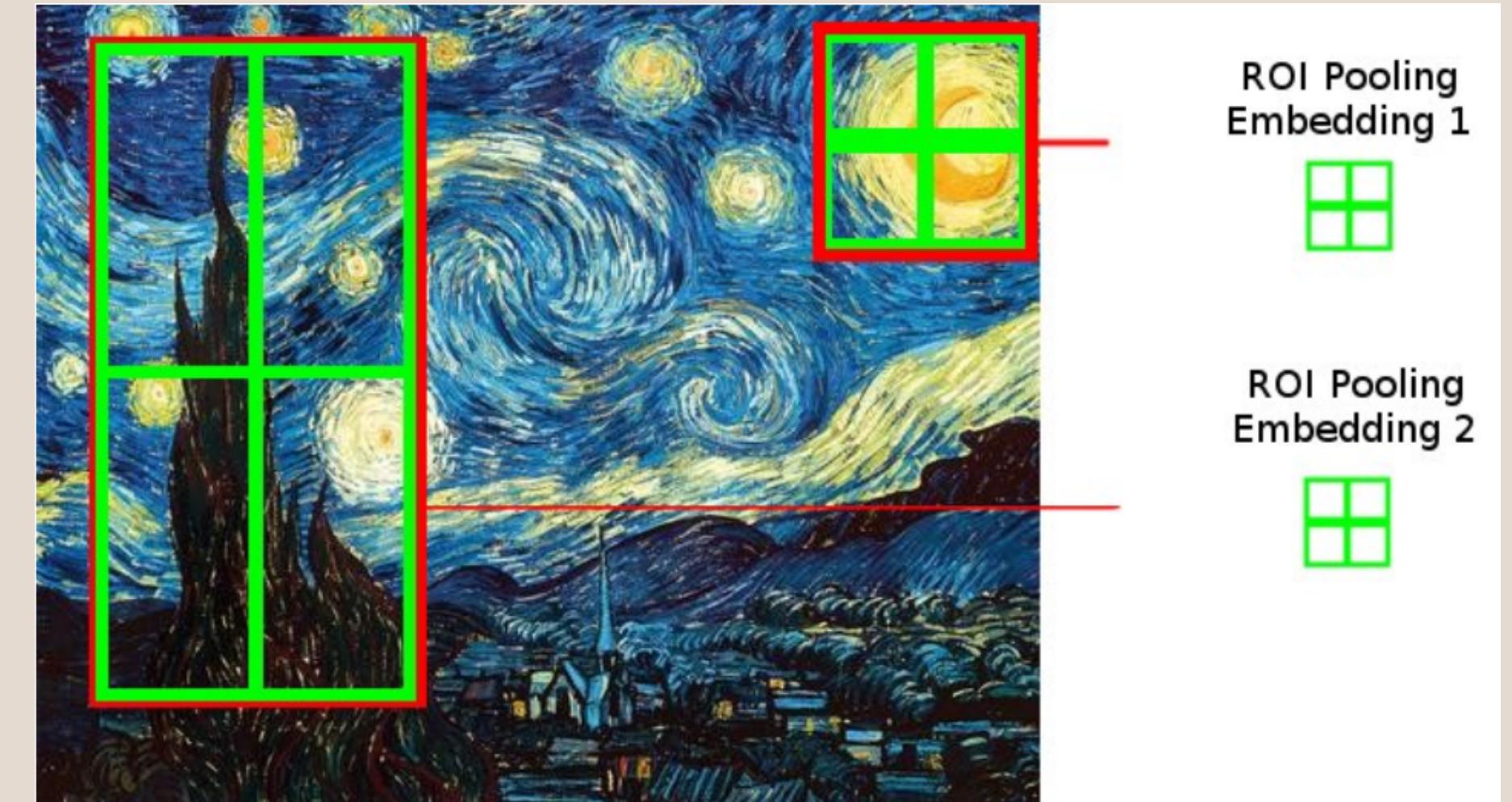
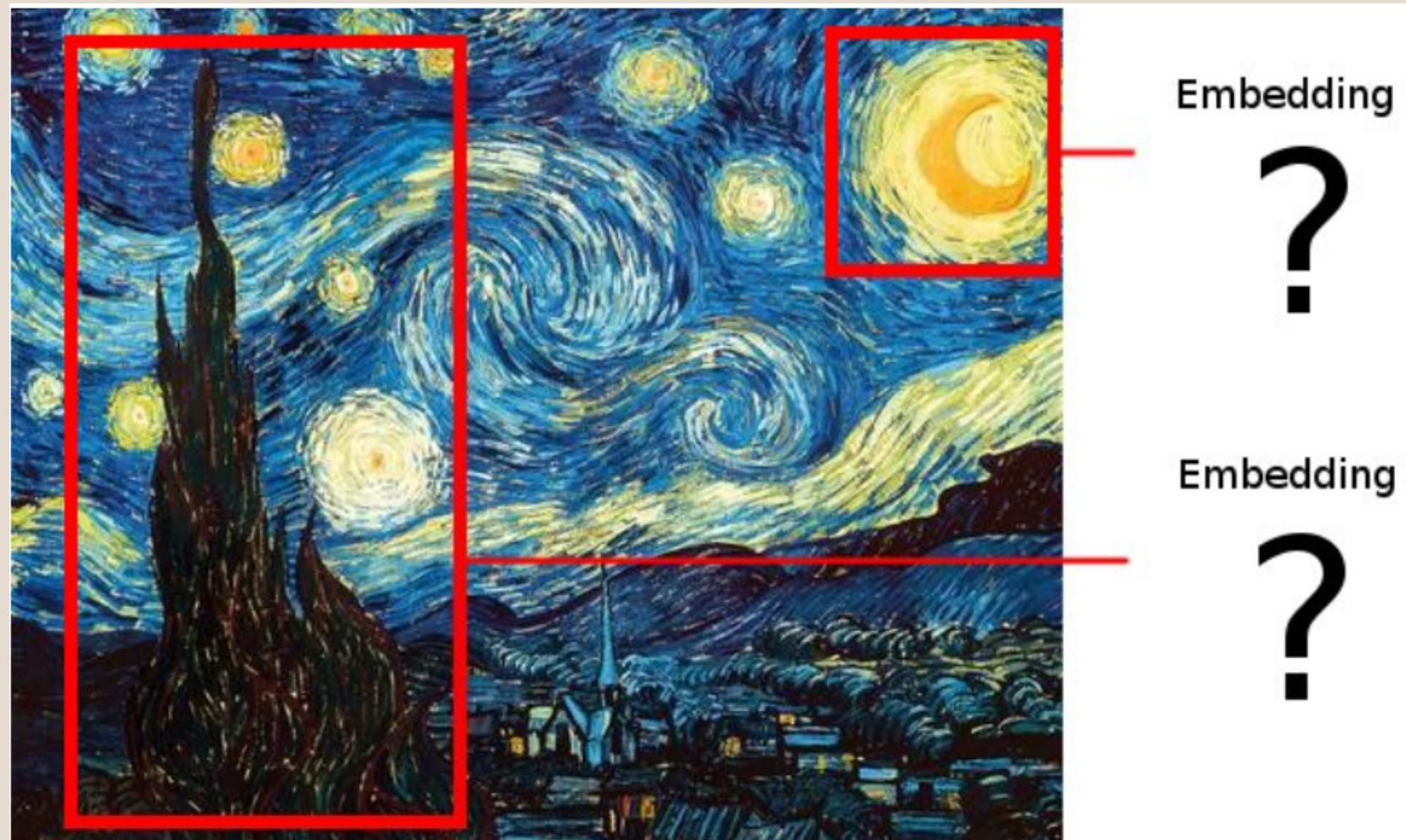
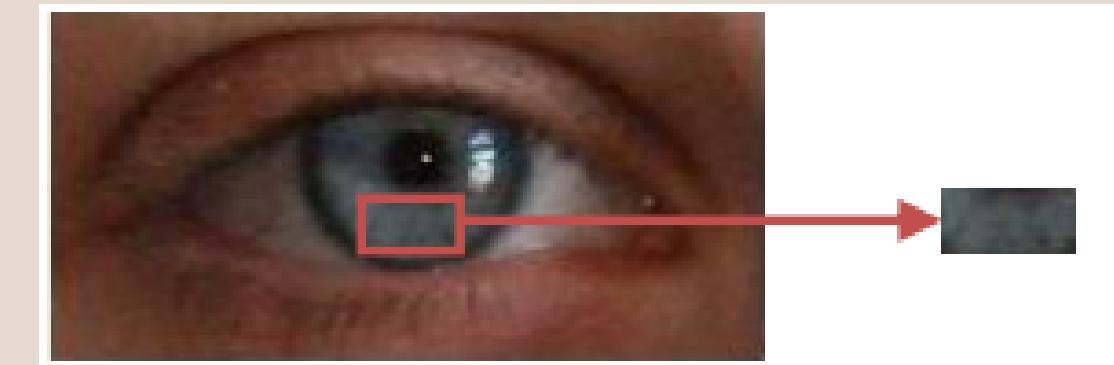
- a. Original image
- b. Converted to grayscale
- c. After filling operation
- d. Detected vertical edges



- e. processing vertical edges and the detected iris circle
- f. Extracted iris
- g. Difference image with reflections
- h. Final iris image

reference: On the Reliability of Eye Color Classification as a Soft Biometrics Trait

# ROI extraction

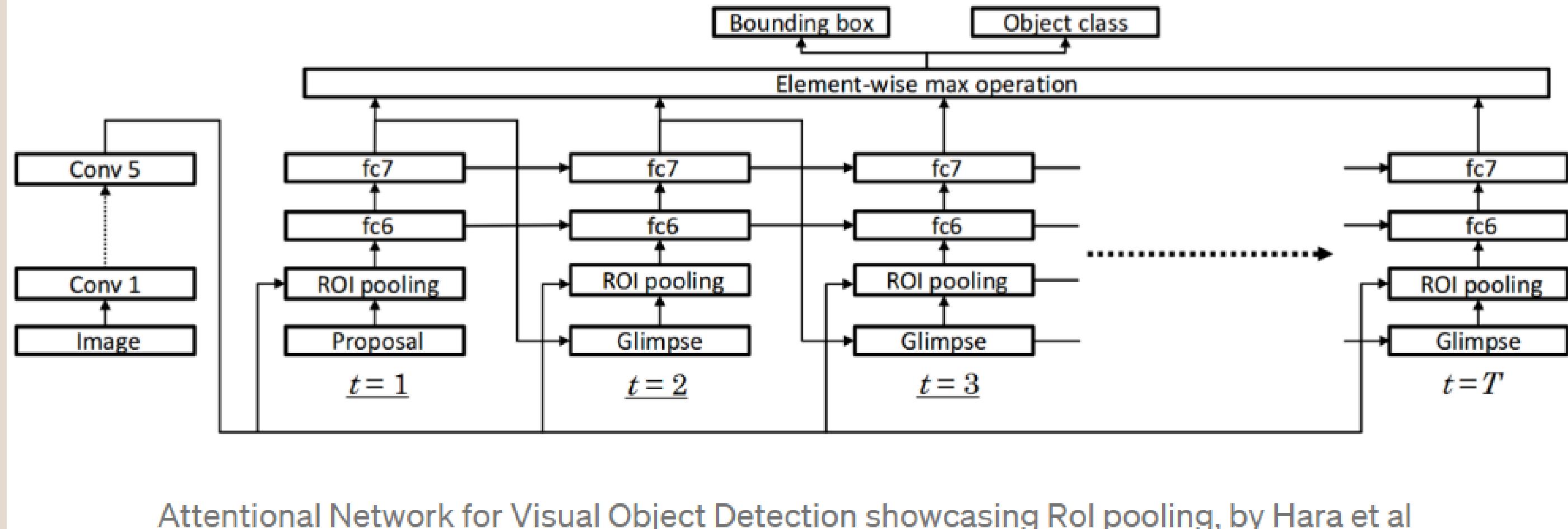


reference: <https://medium.com/xplore-ai/implementing-attention-in-tensorflow-keras-using-roi-pooling-992508b6592b>

# ROI extraction



Fig. 1. Humans have the capability of analyzing image content for visual object detection from multiple fixation points.



[Attentional Network for Visual Object Detection](#) showcasing ROI pooling, by Hara et al

reference: <https://medium.com/xplore-ai/implementing-attention-in-tensorflow-keras-using-roi-pooling-992508b6592b>

# Color analysis

→

1. If black pixels  $\geq 70\%$  -> Black
2. If black is the majority,  $\leq 50\%$  -> second strongest color
3. If black is the majority,  $\leq 50\%$ , and brown == green -> Green

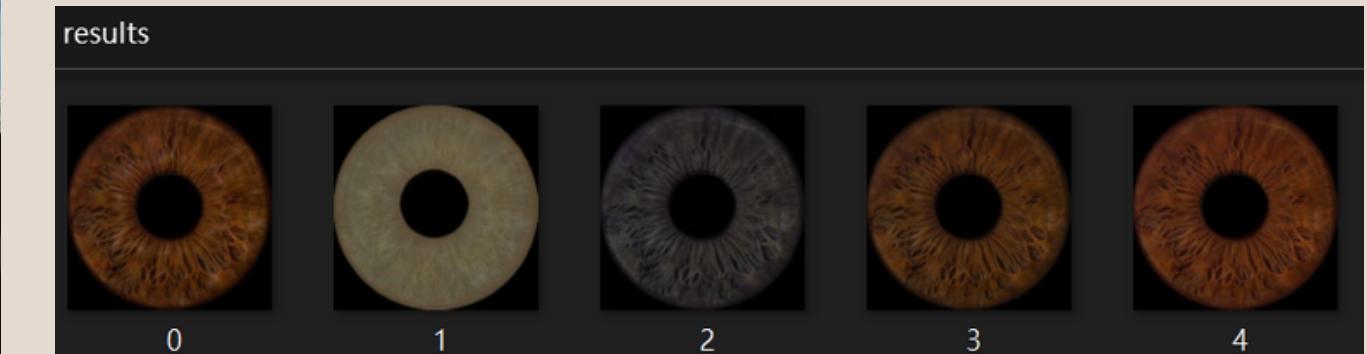
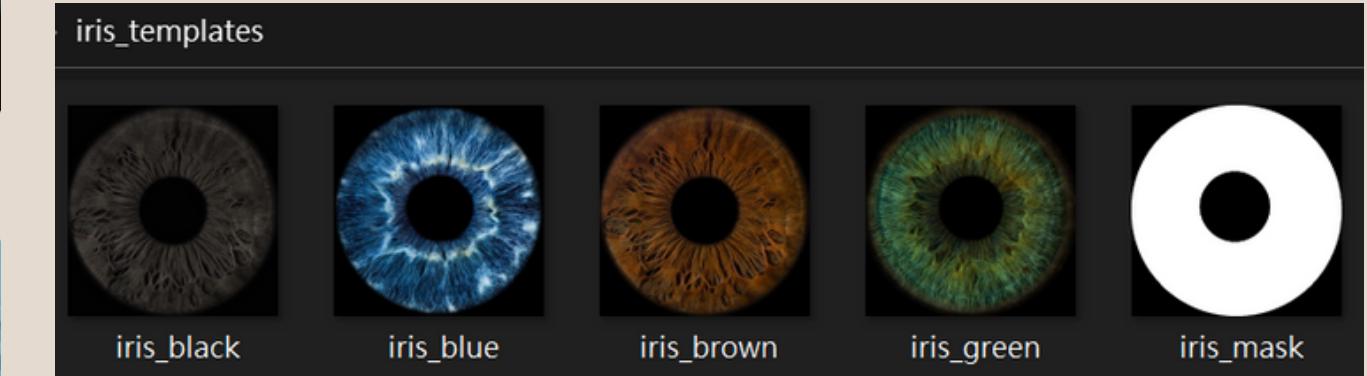
Det \ Real	Black	Brown	Green	Blue
Black	90.9%	5.26%		6.25%
Brown		89.47%	14.28%	
Green	4.54%		78.57%	18.75%
Blue	4.54%	5.26%	7.14%	75%

“The UBIRIS.v2: A Database of VisibleWavelength Iris Images Captured On-The-Move and At-A-Distance,”

# Iris extraction related work →



```
└ pretrained_models
  └ 79999_iter.pth
  └ mmod_human_face_detector.dat
  └ shape_predictor_68_face_landmarks.dat
```



reference: <https://github.com/vanquish630/ExtractIris>

# Testing dataset

→

- US criminal photos, eye color are labeled.  
<https://www.kaggle.com/datasets/davidjfischer/illinois-doc-labeled-faces-dataset>
- Statistics for eyes:
  - 51714 Brown -> Dark
  - 7808 Blue
  - 4259 Hazel -> Brown
  - 2469 Green
  - 1382 Black -> Dark
- Accuracy = 0.4642857142857143 -> 0.7193877551020408



# RESULT & ERROR ANALYSIS

	BASELINE 1	BASELINE 2	MODEL
ACCURACY	0.436681222	0.3755458515	0.7193877551
TESTING DATA	430	430	430

- BL 2 is worse than BL 1, pupil not will detected
- Dataset divergence.
- Influential factors: Illumination, glasses, L/R eye.
- GMM for classification RGB -> HSV

# REFERENCE



## BASELINE 1

<https://github.com/ghimiredhikura/Eye-Color-Detection>

## BASELINE2

<https://github.com/weblineindia/AIML-Pupil-Detection>

## MODEL

<https://github.com/vanquish630/ExtractIris>  
On the reliability of eye color as a soft biometric trait -- Antitza Dantcheva; Nesli Erdoganmus; Jean-Luc Dugelay

<https://medium.com/xplore-ai/implementing-attention-in-tensorflow-keras-using-roi-pooling-992508b6592b>

# DEMO





# SKIN COLOR

# EYE COLOR

# GENDER

# FACE SHAPE

- add more race label
  - Use a better face detection model (faster rcnn)
- 
- use RGB color space
  - decrease illumination variation
- 
- sexual and gender diversity
- 
- try to compare KNN and CNN
  - increase quantity of labels
  - extend training to with/without glasses



## Future Work

1. photo to video
2. website, database
3. keep track of user and change their choice cause all some features are subjective
4. add more features

# Contribution



109550031 李曼融  
face shape recognition



109550027 紀竺均  
eyes color recognition



109550005 張可晴  
race analysis



109550097 周彤瑾  
gender classification

# THANK YOU

