

# CPS803 - Final Project

Face detection and blurring through Machine Learning

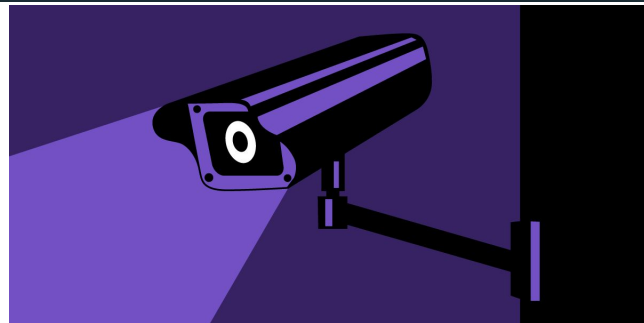
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# INTRODUCTION



The prevalence of public surveillance raises concerns for the privacy of citizens and instances of potential noncompliance with anonymity laws for corporations.

Our goal is to develop deep-learning algorithms that we learn through the CPS 803 course that can detect a face and subsequently apply a dynamic face-blurring filter. Our algorithms should be able to do this for both still and live images.

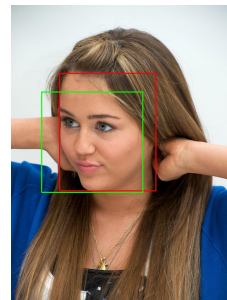
# PROJECT OVERVIEW

- 1) **Dataset:** Wider Faces dataset
  - a) From the University of Hong Kong



- 2) **Models Used**
  - a) Haar Cascade
  - b) HOG SVM
  - c) CNN model (inc.)

- d) DNN w/res10
- e) DNN w/caffe



- 3) **Blurring Algorithm (Gaussian)**

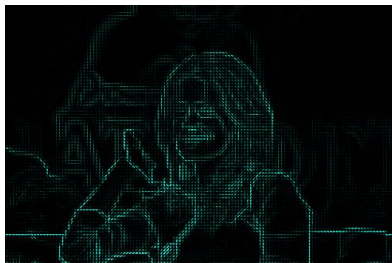
# DATA PREPROCESSING



- Normalizing the image to the CV\_8U data type (unsigned 8 bit integer), ensuring colour values are between 0 to 255.
- Ingesting the data set's ground truth bounding boxes from a text file
- Haar-Cascades: Required converting the images to grayscale.
- DNN: Required resizing images to 300x300 pixels.
- CNN: Required resizing images to a constant dimension of [218, 178, 3] and normalizing by dividing them by 255.

# FEATURES SELECTION

- The **Haar Cascades model** achieves feature selection via a modified AdaBoost of weak learners on a single feature
- Our **HOG SVM model** made use of HOG gradients, where cells of pixels in images where used to compute gradients that were used as a precursor to facial landmark location.



- Our **DNN** and **CNN models** made use of facial landmark locations as input for its features

# DATASET SPLIT

- The dataset used for the pre-trained models did not require splitting into training and validation sets as the models were ready to be tested.
- As a result the testing dataset was split into two categories:
  - Images containing a single visible face
  - Images containing no visible faces
- This allowed us to test for True Positives, True Negatives, False Positives and False Negatives.

# PERFORMANCE METRIC

- Mean Average Precision: The Intersection over Union of the bounding box results. IoU threshold of 0.5 to determine whether result is a False Positive or True Positive.
- Ground Truth Accuracy: The area of coverage of the detected bounding box in comparison to the ground truth, given as a percentage.

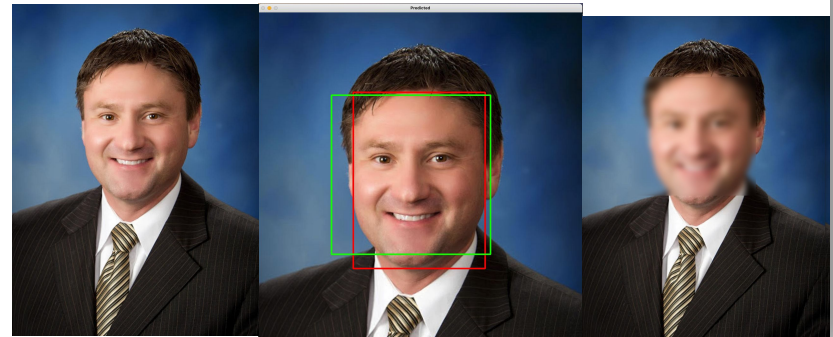
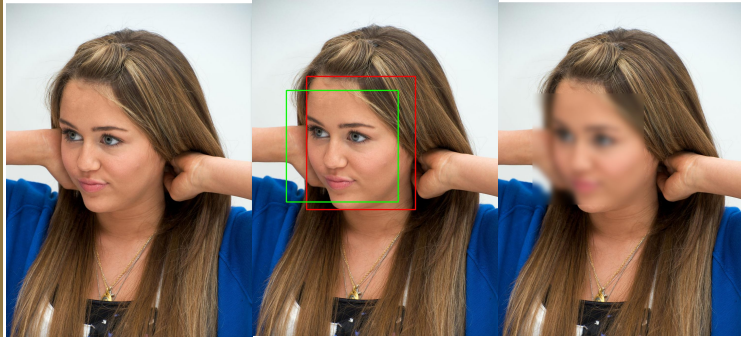
# POST PROCESSING – GAUSSIAN BLUR

- Gaussian blur with a pixel mask of 75x75 was applied to the regions of the image within the detected bounding box.
- Works by sampling all pixels within a  $\pm 75/2$  pixel range in the x and y direction of the center pixel and averaging the intensity.
- Works well for lower resolution images but does not blur adequately for higher resolution images as pixel mask is too small.
- Future work includes an adjustable pixel mask that is proportional to the image resolution.



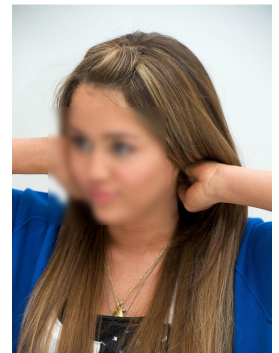
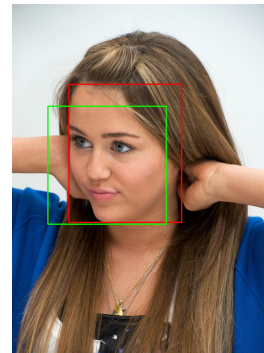
# Haar Cascades

- Object detection through the use of Integral Image.
- Computationally cheap and fast in comparison with other object detection models.
- Pixel Values are determined via the sum of previous pixels to left and above.
- Prone to False Positives at a rate much higher than other models.

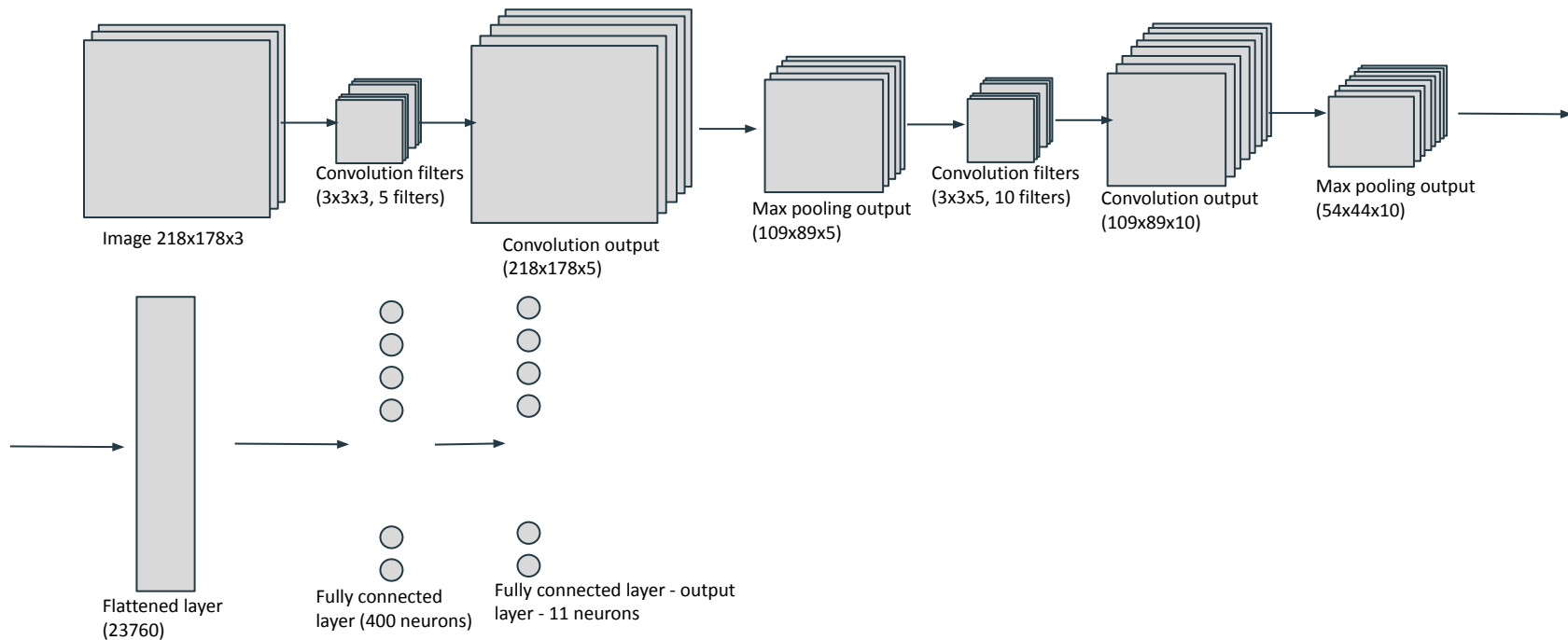


# HOG-SVM

- HOG SVM: Uses Histogram oriented gradients divided into cells and bins to determine the shape as well as the edges (direction preserving) in the image.
- Gradients are grouped into bins, with larger gradients carrying more weight in their respective bin.



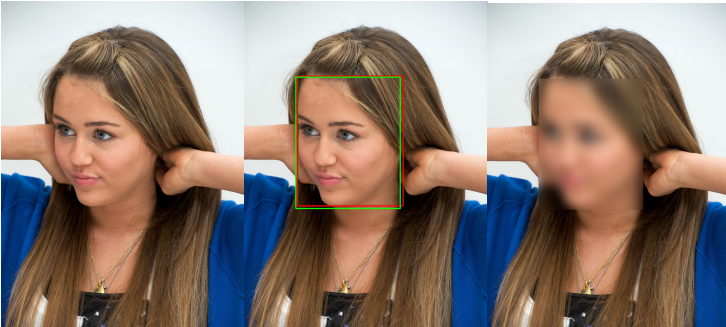
# Convolutional Neural Network (CNN)



# Deep Neural Network

- OpenCV's Res10 and Face-Detector Model, both models are based off of the DNN structure but are trained separately.
- The inclusion of two separately trained models of the same type was to test for consistency in results as both DNN models boasted very high precision.

res10



face-detector

