Drowsiness Detection

General Assembly DSI 31
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INTRODUCTION

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INTRODUCTION

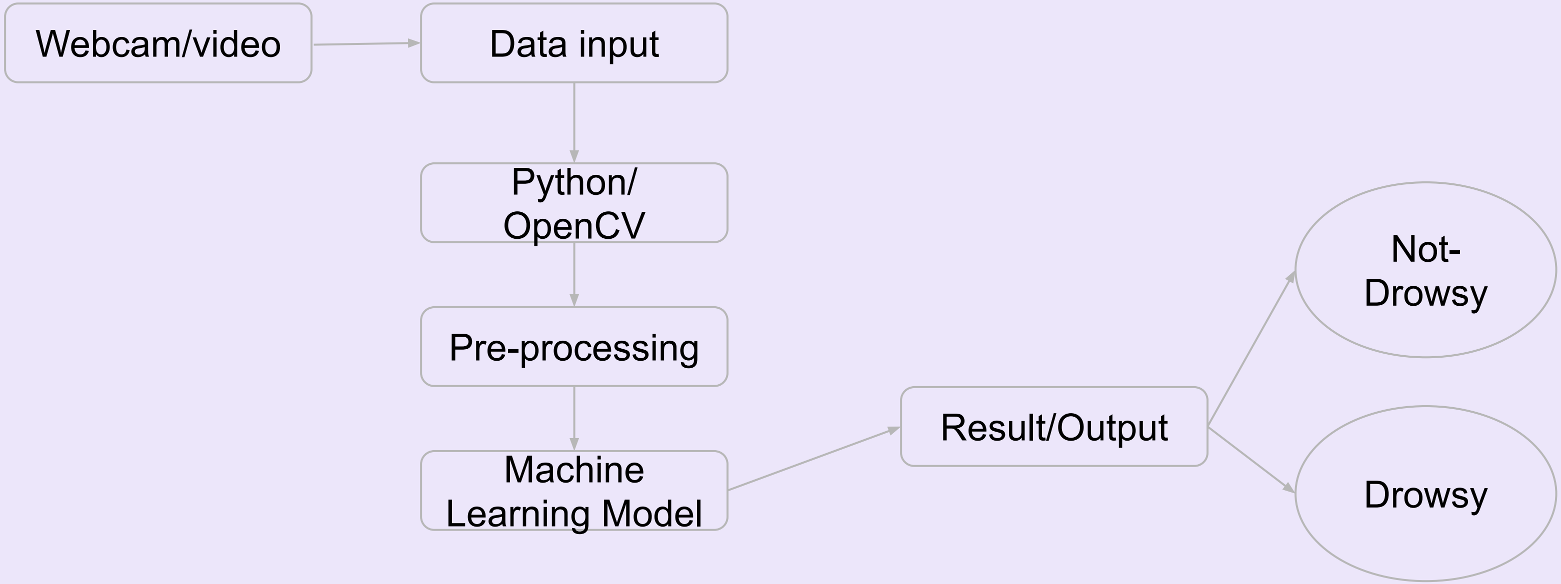
singaporeans rank among the world's sleepiest people. (in 2022)
In fact, Singapore ranks first among the 43 cities evaluated in a recent survey for having the least amount of sleep.

Drowsy driving is a factor in 1 in 4 auto accidents, and 1 in 25 adult drivers say they have dozed off behind the wheel in the previous 30 days. (US Study)

Problem Statement

- To develop a prototype drowsiness detection system that can correctly and instantly track whether a driver is drowsy or not based on some of the facial features.
  As attempting to identify signs of drowsiness early on will help reduce the incidence of accidents if the driver is informed of them.

Methodology



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Dataset

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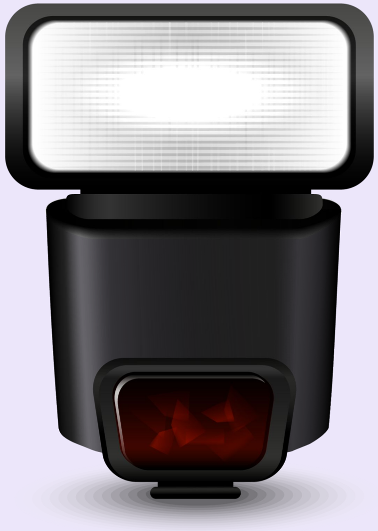
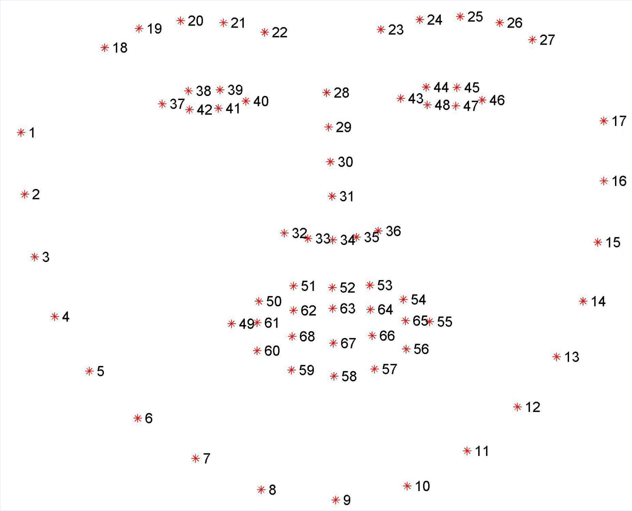
Dataset



The dataset consists of around 30 hours of videos of 61 unique participants including myself.

Using openCV , was able to extract facial landmarks from 45 videos of 23 participants

Predefined Functions



Dlib:

- It’s a landmark’s facial detector with pre-trained models.
- Dlib is used to estimate the location of 68 coordinates (x,y) that map the facial points on a person’s face.

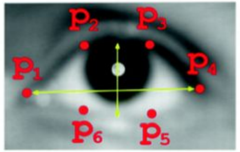
Predefined Functions

Eye Aspect Ratio (EAR):

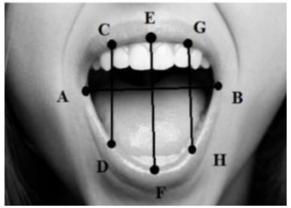
- The proportion of eye length to eye width.
- Two separate vertical lines are averaged across the eyes to determine their length
-

Mouth Aspect Ratio (MAR):

- The proportion of mouth length to mouth width.
- Similar to EAR, two separate vertical lines are averaged across the mouth to determine their length



$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

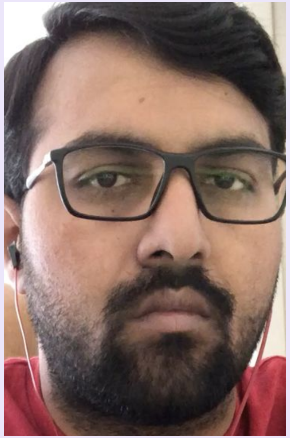
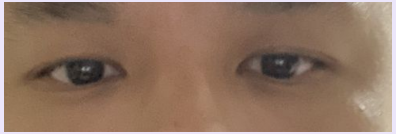


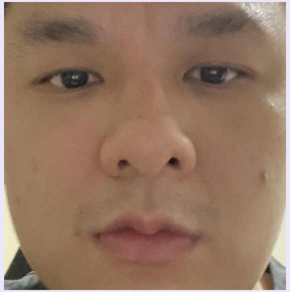
$$\mathrm{MAR} = \frac{|EF|}{|AB|}$$

Data-Cleaning

Eyes open

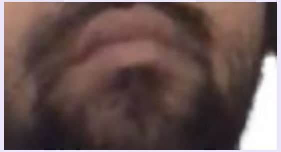


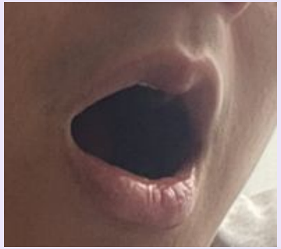





Data-Cleaning

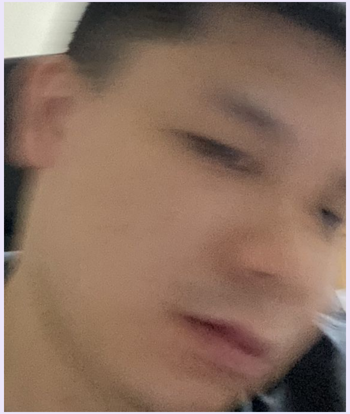
Eyes slightly close

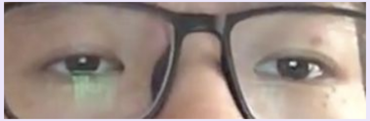




Data-Cleaning

Challenges




EDA

- Each individual has different core features in their default alert state.
- Different lighting conditions may disrupt the detection performance
- EAR will be small while MAR will be big

Feature Engineering

MAR / EAR (MOE):

- Simply the ratio of the MAR to the EAR.
- More responsive to changes than EAR and MAR

$$MOE = \frac{MAR}{EAR}$$

Mouth Over Eye Ratio (MOE)

Pupil Circularity (PUC):

- A measure complementary to EAR but it places a greater emphasis on the pupil instead of the entire eye.
- Similar to EAR, it was hypothesized that tiredness would result in a decrease in a person's pupil circularity.

$$Circularity = \frac{4 * \pi * Area}{perimeter^2} \qquad Area = \left(\frac{\text{Distance(p2, p5)}}{2}\right)^2 * \pi$$

$$Perimeter = Distance(p1, p2) + Distance(p2, p3) + Distance(p3, p4) + Distance(p4, p5) + Distance(p5, p6) + Distance(p6, p1)$$

03

Model

Contents:

Models used

1. Logistic Regression
2. Naive Bayes
3. KNN (K-Nearest Neighbors)
4. MLP
5. Decision Tree
6. Random Forest
7. CNN (Convolutional Neural Network)
8. XG Boost

Results

Models / Metrics	Accuracy
Logistic Regression	58.8%
Naive Bayes	54.6%
KNN	77.2%
MLP	72.4%
Decision Tree	74.4%
Random Forest	70.2%
CNN	71.0%
XG Boost	72.2%

Results (After normalising)

Models / Metrics	Accuracy	F1 Score	ROC
Logistic Regression	0.888	0.904	0.933
Naive Bayes	0.865	0.886	0.930
KNN	0.877	0.892	0.936
MLP	0.881	0.895	0.941
Decision Tree	0.900	0.913	0.938
Random Forest	0.890	0.902	0.959
CNN	0.879	0.894	0.50
XG Boost	0.940	0.948	0.975

Further dive in

Models / Metrics	Accuracy	F1 Score	ROC
Logistic Regression	0.888	0.904	0.933
KNN	0.877	0.892	0.936
CNN	0.879	0.894	0.50
XG Boost	0.940	0.948	0.975

Final Model

K-Nearest Neighbor

89% Recall

Features	Random Forest	XGBoost
MOE_N	31.21%	37.16%
MOE	11.30%	14.24%
MAR_N	18.14%	13.55%
MAR	8.10%	8.72%
EAR_N	12.85%	7.52%
EAR	9.78%	8.21%
Circularity_N	3.70%	5.77%
Circularity	4.87%	4.79%

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CONCLUSION

Contents:

1. Conclusion
2. Limitations
3. Future Enhancement

Conclusion

Model Complexity

When performing tasks, less complicated models can be just as effective as more complex ones.But ultimately, it is better to employ the more sophisticated model with a lower false-negative rate than a simpler model.

Feature Importance

We understood that everyone's baseline for the eye and mouth aspect ratios is different which was why normalization was crucial to our performance.

Flexibility of the system

System permits different models to predict the outcome, which could be useful because we could use different models to predict certain attributes based on the system's accuracy.

Limitation

More different training data

For the models, more diverse images taken in a range of seating arrangements and lighting conditions would have been desirable.

Environment

There cannot be any reflective materials behind the driver, which is another limitation. The system becomes more reliable as the background becomes more uniform.

Future Enhancement

More Complex Models

When performing tasks, less complicated models can be just as effective as more complex ones.But ultimately, it is better to employ the more sophisticated model with a lower false-negative rate than a simpler model.

Behavior feature

Like sudden head movements, hand motions, head tilting (posture), or even monitoring eye movements, these are new, distinct signs of tiredness.

Fine-tune Model

How the false-negative rate for kNN and other straightforward models can be reduced.

THANK YOU!

Annex

Annex

1825 — 1936 — 1948 — 1990 — 2004

VENUS

1936

Venus is the second planet from the Sun

JUPITER

1990

It’s the biggest planet in the Solar System

SATURN

1825

Saturn is a gas giant and has several rings

MARS

1948

Despite being red, Mars is a cold place

NEPTUNE

2004

It’s the farthest planet from the Sun

References

VENUS

Venus is the second planet from the Sun

JUPITER

It’s the biggest planet in the Solar System

1825 — 1936 — 1948 — 1990 — 2004

SATURN

Saturn is a gas giant and has several rings

MARS

Despite being red, Mars is a cold place

NEPTUNE

It’s the farthest planet from the Sun

TIPS FOR USING YOUR CAMERA

MERCURY

Mercury is the closest planet to the Sun

VENUS

Venus is the second planet from the Sun

JUPITER

Jupiter is the biggest planet of them all

SATURN

Saturn is a gas giant and has several rings

MARS

Despite being red, Mars is a cold place

LIST OF ACTIVITIES FOR THE DAY

MARS

- insert an activity
- insert an activity
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VENUS

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MERCURY

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