

Abstract

Driver Drowsiness is a significant safety concern which creates a need for reliable systems that can detect signs of drowsiness under varying realistic conditions. This study evaluated the robustness of facial landmark-based indicators, including Eye Aspect Ratio(EAR), Mouth Aspect Ratio (MAR), and head pose(pitch, yaw, and roll values) for drowsiness detection under changes in resolution, lighting, and facial occlusions. Images from a driver drowsiness dataset were evaluated using threshold-based models and a logistic regression classifier. Performance was determined through accuracy, precision, recall, and F1 score. EAR, MAR, and head pose thresholds were determined through finding the best training F1 score. Under baseline conditions, logistic regression achieved an F1 score of 0.714, overall performing better than threshold-based models. Environmental conditions affected measurements of facial features and model performance, with facial occlusions and lighting affecting results more than image resolution. Ultimately, this study’s findings suggest that combining multiple landmark-based indicators using machine learning classifiers may be a more effective approach to driver drowsiness detection than fixed threshold based approaches.

Evaluating the robustness of facial landmark-based indicators for driver drowsiness detection under realistic condition

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Introduction

Drowsy driving is a major contributor to accidents on the road and can impair a driver’s attention, reaction time, and decision-making[1],[2]. Computer vision-based driver monitoring systems can detect signs of drowsiness using facial features such as eye closure, mouth opening, and head position [3],[5]. Facial landmark-based measures such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio(MAR), and head pose estimation are non-intrusive ways to quantify these behavior. However, many existing studies evaluate these methods under controlled conditions, while real-world factors such as lighting, occlusion, and image resolution can affect detection performance [4]. This study addresses this gap by evaluating the robustness of multiple facial landmark-based indicators under varying environmental conditions.

RESEARCH QUESTION: How do changes in brightness, resolution, and occlusion affect the performance of facial landmark-based indicators for driver drowsiness detection?

Methods

Face Image -> Face Landmarks -> Facial Measurements -> Classifier -> Drowsy/Not Drowsy

Dataset:

- Kaggle Driver Drowsiness Image Dataset [8]
- 25 drowsy + 25 non drowsy images selected per subject
- Images tested under varying brightness, occlusion and resolution (using functions on OpenCV to alter images)

Facial Landmarks/Features:

- Facial landmarks extracted using MediaPipe [9]
- EAR measures eye openness [6]
- MAR measures mouth opening[10]
- Head pose: measured by Euler angles pitch, yaw, and roll calculated using OpenCV PnP [7]

Classification Methods:

- Threshold-based - predefined EAR, MAR, and head-pose thresholds (chosen by using values that maximized F1 scores)
- Logistic regression - combines all 5 indicators (EAR, MAR, pitch, yaw, and roll) in order to allow for comparison of indicators
- Training and testing sets were separated by subject, preventing images from the same subject from appearing in both sets

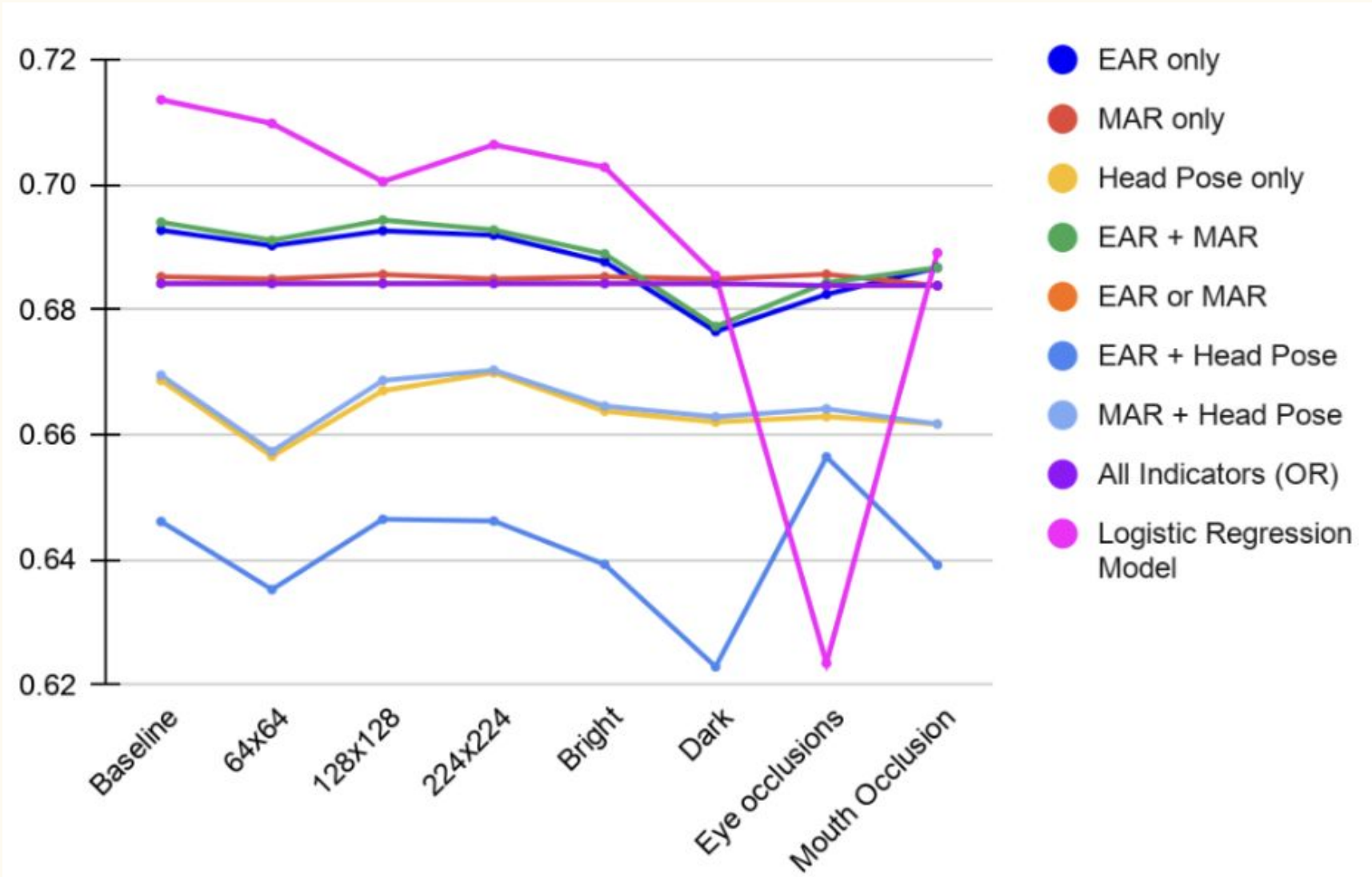
Evaluation:

- models compared using accuracy, precision, recall, and F1 score across environmental conditions

Results

- Logistic regression achieved the highest baseline F1 score (0.714), but it dropped to an F1 score of 0.624 when eye occlusions were added
- EAR + MAR threshold had second highest baseline F1 score, followed by EAR alone
- Models using MAR and/or head pose performed similarly and generally lower than models incorporating EAR
- EAR had the largest-magnitude coefficient of 0.991
- Among resolutions, performance was lowest in 64x64 and also decreased more under dark lighting than in bright lighting compared with normal conditions
- Eye occlusions caused a greater performance decrease than mouth occlusions

F1 Scores Across Different Conditions for Different Models



LOGISTIC REGRESSION STANDARD COEFFICIENTS UNDER BASELINE CONDITIONS	
Indicator	Coefficient
EAR	-0.991352
MAR	0.504616
Pitch	0.359386
Yaw	0.342030
Roll	0.186782

Discussion

- Eye-based features were the most reliable indicators of drowsiness as models with EAR generally performed better than those relying on MAR or head pose
- Strong performance of EAR suggests changes in eye openness are a more consistent sign of drowsiness than mouth opening or head position, which can be attributed to the fact that mouth opening can also be related to talking and head pose can be indicative of looking at the road rather than drowsiness
- Environmental conditions affected reliability with dark lighting and eye occlusion reducing performance significantly
- Relatively similar performance across resolutions suggest high-resolution images may not be necessary for effective detection which could be useful for systems that have limited computational resources

Conclusion

- Facial landmark-based features can effectively identify signs of driver drowsiness, with EAR as the strongest indicator
- Environmental conditions, particularly eye occlusion and dark lighting significantly reduced model performance
- findings highlight importance of testing drowsiness detection under realistic conditions

Limitations + Future work:

- dataset contained limited number of subjects, may not represent all real-world conditions
- future research should test models on larger, more diverse and real-time driving datasets and additional environmental conditions rather than image dataset

References

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