Detecting Drowsiness in Automobile Drivers

Preventing Accidents by Identifying Behavior Associated with Drowsiness

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ABSTRACT

Accidents caused at least partially by drowsy drivers are one of the major causes of preventable deaths globally. The goal of this project is to use machine learning to evaluate the alertness of an automobile driver and to provide feedback to the driver about whether or not they should be driving.

CCS CONCEPTS

• Applied Computing • Life and Medical Sciences • Consumer Health

KEYWORDS

machine learning, convolutional neural networks, driver safety, drowsy, tired, alert, real-time, video, analysis

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1 Introduction

According to a poll taken by the CDC in 2009-2010, over 4% of drivers admitted to having fallen asleep while driving within the past 30 days [1]. Furthermore, an estimated 16.5% of fatal accidents involve drowsy drivers [2]. Drivers falling asleep seems to be a pressing issue that needs to be addressed to mitigate further unnecessary loss of life. The goal of this project is to provide one potential solution to this pressing issue.

We want to provide a highly accurate machine learning model that can detect drowsiness in real time based on a video feed, with all data processed on-device, so that there are no potential privacy concerns involved in using the machine learning model. We then intend to use the classifications that the model outputs over time to alert the driver that they should not be driving, currently.

In this project, we will use machine learning image classification techniques (e.g. convolutional neural networks) to classify whether or not a driver is tired based on a real-time video feed of the driver's facial expressions and head positions over time.

Our classifier model needs to be computationally conservative, so that it can be run on a small, cheap computer, like a Jetson Nano or Raspberry Pi 3/4. Future work may involve designing a casing to contain such a computer running our model, with a built-in alarm to wake drowsy drivers, and even potentially a built-in motion sensor to detect vehicle weaving, which could serve as another indicator of drowsiness.

2 Related Work

2.1 Drowsiness Estimation Using a Heart Rate Sensor

Lakshmi Priya et al. [3] monitor a heart rate sensor to determine whether or not to turn on the camera and check for signs of drowsiness. They determine drowsiness using the eye aspect ratio (EAR) which is a measure of how open or closed the eyes of the driver are.

This study is different from our planned work in a couple of big ways. First, this related work uses a heart rate sensor. Our proposed work does not. We are trying to design something that requires as little pre-driving setup as is possible. Second, this related work stores data about the user on the cloud. Again, we have no plans to go this route for privacy reasons.

2.2 Drowsiness Estimation using Respiratory Monitoring

Guede-Fernández et al. [4] attempted to detect drowsiness using respiratory monitoring. The method used to measure breathing over time was respiratory inductive plethysmography (RIP).

This setup requires the monitored driver to wear a respiration-monitoring harness. While this study yielded decent results (Cohen's Kappa agreement score of 0.75± 0.19), the pre-driving setup required makes this drowsiness detection method so inconvenient that we do not believe it can be successfully scaled to be used by the general population.

2.3 Drowsiness Estimation using Vehicle Metrics

Knipling & Wierwille [6] evaluated the ability of several vehicle motion metrics to determine driver drowsiness levels. They found that the standard deviation of the lateral position of the vehicle relative to the lane is the single strongest predictor of driver drowsiness.

Factor Name	Definition	B Weight	P-Level
INTACDEV	Standard deviation of the high-pass lateral velocity of the vehicle.	-0.109	< 0.0005
LANDEV	Standard deviation of lateral position relative to the lane.	+0.873	< 0.0005
LNERRSQ	Mean square of the difference between the outside edge of the vehicle and the lane edge when the vehicle exceeds the lane. When the vehicle does not exceed the lane the contribution to the measure is zero.	-0.258	< 0.0005
STEXED	Proportion of time that steering velocity exceeds 150” per second.	+0.090	0.007
NMRHOLD	Number of times that the steering wheel is held still for 0.4 second or longer.	-0.204	< 0.0005
THRSHOLD	Proportion of time that the steering wheel is held still for 0.4 second or longer.	+0.250	< 0.0005

Source: Wreggit, Kirn, and Wierwille, 1993

Once our planned image classification algorithm is completed and tested, we may add an accelerometer to our setup to measure the change in lateral position over time. We could potentially use this information in our study as a second indicator of driver drowsiness.

2.4 Review of Available Methods

Sahayadhas et al. [5] reviews known methods for detecting drowsy drivers. The first proposed method of detection is through driving style or vehicle movement data. This includes information about how the is steering or accelerating.

The second proposed method of detection is via the driver's behavior. This could include detecting things like eyelids drooping, yawning, or head slowly dropping due to overly relaxed muscles.

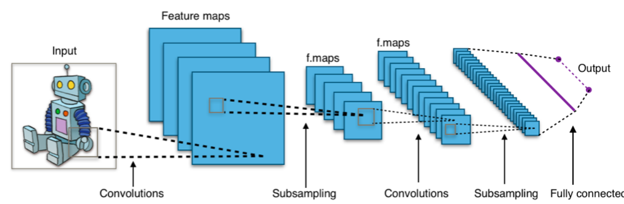
The third proposed method of detecting drowsy drivers is through physiological changes, like changes in heart rate or eye movement speed (rapid or slow eye movement).

3 Proposed Work

In real-time, we will acquire and process video of the driver's face and head positions. Then we will split the video into frames and use a machine learning model to classify each image as drowsy or not drowsy.

We will do this by identifying key facial characteristics using image segmentation and then measuring key features like eye aspect ratio (i.e. how open or closed the driver's eyes are). Other interesting metrics like the amount of time per blink or the resting position of the head may also be evaluated.

Currently, we are planning on using convolutional neural networks for image segmentation and drowsiness classification.



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Convolutional neural networks (CNNs) use layers of learned “slides” to essentially condense small parts of images into a summarizing set of numbers. [7] This process is repeated over and over until the result is fed into a fully-connected artificial neural network to output the image classification or regression (depending on the use case). This process allows the CNN to learn to identify complex features in images, without using the incredibly large number of neurons that a fully-connected artificial neural network would need to have to solve the same classification/regression problem.

The dataset we will be training our CNN model on contains 2467 images for training, split evenly between eyes open, eyes closed, yawning, and not yawning. Further, we also have access to a testing dataset that contains 433 images, also evenly split between the four classes represented in the training dataset. While our train and test datasets are split evenly between these datasets, in real life the split between drowsy and non-drowsy drivers will not be balanced - there will be more non-drowsy drivers in actual use than there will be drowsy drivers. This presents some potentially interesting challenges for evaluating our model.

4 **Evaluation**

Our CNN model will be tested on a dataset of 430 images that the model was not trained on. The evaluation metric used will be a precision-recall curve, because this evaluation metric is well-suited for imbalanced data, and the real-life use of our project absolutely represents an imbalanced dataset.

Most of the time, drivers will not be falling asleep. But even though sleepy drivers are infrequent, the damage caused by sleepy drivers is significant. As a result, it is crucial that we successfully classify sleepy drivers even though most drivers are sleepy very infrequently.

5 **Milestones**

See the table below for information about our milestones for this project.

Date	Milestone	Status
Sep 29, 2021	Proposal	Complete
Oct 1, 2021	Presentation	In Progress
Oct 15, 2021	Training Set Augmentation	Incomplete
Oct 21, 2021	Image Segmentation	Incomplete
Oct 25, 2021	Model Training (First Iteration)	Incomplete
Nov 1, 2021	Project Checkpoint	Incomplete
Nov 8, 2021	Model Optimization	Incomplete
Dec 6, 2021	Model Testing and Deployment	Incomplete

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