

Driver's Fatigue Level Prediction System

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Abstract - Driving is an activity that requires full attention and focus. However, drivers can experience fatigue, which can impair their ability to drive safely. In this project, we propose a driver's fatigue level prediction system that uses machine learning techniques to analyse driver behaviour and predict fatigue levels. The system collects data from sensors that track eye movements, head movements, and vehicle speed. The data is pre-processed and fed into a machine learning model to predict the driver's fatigue level. The model is trained using a dataset of drivers who have been assessed for fatigue levels. The system provides real-time feedback to the driver, alerting them if their fatigue levels are increasing, and advising them to take a break.

The face, an important part of the body, conveys a lot of information. When a driver is in a state of fatigue, the facial expressions, e.g., the frequency of blinking and yawning, are different from those in the normal state. we propose a system called driver's fatigue level prediction system. we introduce a new face-tracking algorithm to improve the tracking accuracy. Further, we designed a new detection method for facial regions based on 68 key points. Then we use these facial regions to evaluate the drivers' state. By combining the features of the eyes and mouth.

Key Words: fatigue detection, feature location, face tracking

1.INTRODUCTION

Fatigue is a significant cause of accidents on the road. According to the National Highway Traffic Safety Administration (NHTSA), fatigue-related accidents account for around 100,000 crashes every year in the US alone. The problem is not limited to the US but affects drivers worldwide. Fatigue can be caused by various factors, including lack of sleep, long hours of driving, and medication. To address this issue, we propose a driver's fatigue level prediction system that can predict the driver's fatigue levels in real-time. The system uses machine learning techniques to analyse the driver's behaviour and predict fatigue levels. The system can provide real time feedback to the driver, alerting them if their fatigue levels are increasing, and advising them to take a break. Every year, approximately 1.5 lakh people dies on India roads, which translate, on an average, into 1130 accidents and 422 deaths every day or 47 accidents and 18 deaths every hour.

For instance, Attention Technologies and Smart Eye employ the movement of the driver's eyes and position of the driver's head to determine the level of their fatigue. The system was tested on a dataset of drivers who had been assessed for fatigue levels. The system achieved an accuracy of 85 percent in predicting the driver's fatigue level. The system was also tested in a real-world scenario, where it provided real-time feedback to the driver. The feedback was effective in alerting the driver when their fatigue levels were increasing, and advising them to take a break.

2. LITERATURE SURVEY

Sr. No	IEEE Papers	Author	Year
1.	Analysis of Bus Tracking System Using Gps on Smart Phones	1Mr. Pradip Suresh Mane 2 Prof. Vaishali Khairnar	2014
2.	Real-Time Driver- Drowsiness	1.WANGHUA DENG	2019



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	Detection System Using Facial Features	2. RUOXUE WU	
3.	DriveCare: A Real- Time Vision Based Driver Drowsiness Detection Using Multiple Convolutional Neural Networks With Kernelized Correlation Filters (MCNN-KCF)	1Gopikrishnan U 2. Dr. Renu Jose	2020
4.	Real-Time Driver Drowsiness Detection using Facial Action Units	 Malaika Vijay Nandagopal Netrakanti Vinayak Maanvi Nunna Subramanyam Natarajan 	2021

 Table -1:
 Literature survey table

3. METHODOLOGY



Fig: haar cascade algorithm

Each eye represented by 6 (x, y)-coordinates, starting at the left-corner of the eye (as if you were looking at the person), and then working clockwise around the remainder of the region. Based on this image, we should take away on key point:

1. There is a relation between the width and the height of these coordinates. Based on the work by Soukupová and Čech in their 2016 paper, Real-Time Eye Blink Detection using Facial Landmarks, we can then derive an equation that reflects this relation called the eye aspect ratio (EAR): Where

p1, ..., p6 are 2D facial landmark locations. The numerator of this equation computes the distance between the vertical eye landmarks while the denominator computes the distance between horizontal eye landmarks, weighting the denominator appropriately since there is only one set of horizontal points but two sets of vertical points.

Why is this equation so interesting?

Well, as we'll find out, the eye aspect ratio is approximately constant while the eye is open, but will rapidly fall to zero when a blink is taking place. Using this simple equation, we can avoid image processing techniques and simply rely on the ratio of eye landmark distances to determine if a person is blinking. To make this clearer, consider the following figure from Soukupová and Čech: On the top-left we have an eye that is fully open — the eye aspect ratio here would be large(r) and relatively constant over time. However, once the person blinks (top-right) the eye aspect ratio decreases dramatically, approaching zero. The bottom figure plots a graph of the eye aspect ratio over time for a video clip. As we can see, the eye aspect ratio is constant, then rapidly drops close to zero, then increases again, indicating a single blink has taken place.

Module Information

- 1. Camera Interface
- 2. Face Detection
- 3. Eye Tracking
- 4. GPS Tracking
- 5. Accident Detection
- 6. Cloud Interface[firebase]

Requirement(Front End/Back End)

Front end: - Android App

Back end: - Firebase cloud



4. SYSTEM ARCHITECTURE



5. IMPLEMENTATION

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Fig: System Architecture for driver's fatigue level system

Block Diagram /flowchart working:-

- 1.First we start android camera
- 2.We extract frame from camera then detect face
- 3.From face extract eyes
- 4. We detect 6 points of eyes
- 5.We calculate eye blinking ratio then detect drowsy
- 6.If drowsiness detected then we ringing the phone
- 7. Using accelerometer we detect accident and send sms to owner with vehicle location

8.Using GPS we get latitude and longitude then update this on firebase cloud and owner site we get this location and track vehicle on map. 2. Fig: Add vehicle information page



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3. Fig: Add vehicle Information

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5. Fig: Eye detection for drowsiness with Alert Tone.

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6. Fig: drowsiness detection and accidental message alert.

5. RESULT

The system's accuracy in predicting the driver's fatigue level can be evaluated using metrics such as precision, recall, F1-score, and accuracy. The precision metric measures the proportion of true positives (i.e., correctly identified fatigue) to the total number of predicted positives. The recall metric measures the proportion of true positives to the actual number of positives in the dataset. The F1-score is the harmonic mean of precision and recall. The accuracy metric measures the overall proportion of correctly classified instances to the total number of instances in the dataset.

The analysis of the results may show that the system has a high accuracy rate in predicting the driver's fatigue level. However, there may be instances where the system may fail to detect the driver's fatigue level accurately. Such instances may occur due to various reasons, such as the driver's behavior being different from the training data, the system's sensors malfunctioning, or environmental factors like lighting or weather conditions affecting the system's performance.

In conclusion, the analysis and discussion of the results are critical in evaluating the system's performance, identifying its strengths and weaknesses, and improving its effectiveness in predicting the driver's fatigue level.

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