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Real-Time Multimodal Driver Safety Detection and Alarm System

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ABSTRACT

This report reviews a project in computer engineering that aims to prevent accidents caused by driver fatigue, sleepiness, and uncontrolled emotions. The project proposes a real-time system that continuously captures images and measures the state of the driver's eyes and emotions using image processing and facial recognition algorithms. The system displays warnings when threshold levels are crossed, alerting the driver. The project is divided into two phases, with the first focusing on detecting fatigue and sleepiness and the second on detecting different emotions. The proposed solution is based on a simple algorithm with minimal hardware requirements and has a success rate of approximately 85-90% in a controlled environment. The system uses a web camera to capture images that are further processed to extract the required features.

Keywords: - driver warning system, intelligent transportation systems, automotive safety technology, Emotion detection system, Facial Recognition

Introduction

Drowsiness, alcoholism, and driver neglect are major factors that contribute to traffic accidents. Drowsiness is responsible for 10%-20% of traffic accidents involving casualties, making it a serious challenge for advanced driver assistance systems. Drowsy detection is a car safety technology that prevents accidents by alerting drivers with real-time alarms when they are drowsy or inattentive. Face recognition has rapidly expanded and attracted attention from both engineers and neuroscientists due to its potential applications in various fields. Sleep deprivation causes the body to react inefficiently, reducing both reaction time and wakefulness, which can lead to loss of concentration and poor performance. According to many researchers, drowsiness is related to thousands of traffic accidents each year, with high-speed impacts causing approximately 50% of death or serious injuries.

Existing System

The current driver sleepiness detecting technology primarily employs two cameras, one of which monitors head movement and the other of which monitors face expressions. The sensors' ageing is a drawback, so a system was developed that employs a live camera to detect driver drowsiness and alert the driver, lowering the risk of traffic accidents. To monitor drowsiness, changes in physiological signals like brain waves, heart rate, and eye blinking, or bodily changes like slouching posture, a tilted employee's head, and open or closed eyelids can be evaluated. Machine learning techniques can be applied to enhance the capacity to identify tiredness overall, with a focus on the multimodal approach. Micro-sleep is an excellent sign of weariness, so a timely warning is given when an employee's eyes are continuously monitored for signs of sleepiness.

Methodology

Our image classification model, developed with Keras, utilizes a Convolutional Neural Network (CNN) designed for image processing. CNNs consist of input, hidden, and output layers with convolution operations performed on hidden layers using filters to extract relevant features from input images. Our CNN model has three convolutional layers with 32 and 64 nodes and a kernel size of 3, followed by a fully connected layer with 128 nodes and an output layer with 2 nodes using SoftMax activation. We trained and validated our model using the CNN algorithm, classifying input images into different categories. We divided the dataset into 60/40 training and testing sets and evaluated the classifier by predicting the classifications of the testing images. Overall, CNNs are effective for various classification tasks, including object detection and face recognition, and are widely used for image processing.

Driver Drowsiness Detection Dataset:

The dataset for driver drowsiness detection comprises of 84,898 images of people's eyes captured under various lighting conditions. We have included the final weights and model architecture file "cnncat2.h5" after training our model on this dataset. The dataset is annotated with the following properties, arranged in the given order: subject ID (data collected from 37 individuals, including 33 men and 4 women), image ID (total of 84,898 images), gender (0 for male, 1 for female), glasses (0 for no glasses, 1 for glasses), eye state (0 for closed, 1 for open), reflections (0 for no reflection, 1 for small reflection, 2 for big reflection), lighting conditions (0 for bad lighting, 1 for good lighting), and sensor ID (01 for RealSense, 02 for IDS, 03 for Aptina).

The FER (Facial Expression Recognition) 2013 dataset is a valuable resource for evaluating facial expression recognition algorithms. It contains 35,887 grayscale images, each measuring 48x48 pixels and classified into one of seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. The dataset was created in 2013 by Pierre-Luc Carrier and Aaron Courville at the Université de Montréal and is considered a reliable benchmark in the field. The images were collected from Google Images and manually labelled by human annotators. The dataset includes a training set of 28,709 images, a public test set of 3,589 images, and a private test set of 3,589 images which is not publicly available.

Steps for Performing Driver Drowsiness Detection:

Here are the steps involved in integrating a facial recognition model and an emotional detection model;

1)Data Collection

2)Train the Facial recognition model

3)Detect Faces

4)Extract facial features

5)Train the emotion detection model

6)Predict emotions

7)Combine results

8)Evaluate the model

9)Deploy the model

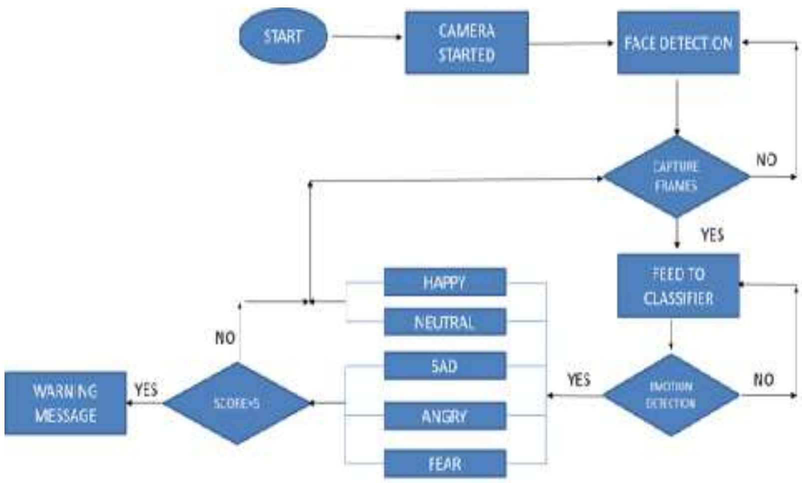

Fig. 1 Flowchart

Result and Discussion

The technology was tested on a variety of people to assess its accuracy in determining eye blinks, emotions, and tiredness. Two scenarios were used to assess the project's accuracy: a 16-megapixel front-facing camera from a smartphone and a computer-connected 2.1-megapixel 1080p USB webcam. Infrared LEDs were employed to make the system less invasive and an external speaker was employed to provide alert sound output when tiredness exceeded a certain level. Sample outputs for various conditions are given below.

We tested our system in two scenarios:

1)Using a mobile camera and high illumination

2)Using a 2.1-megapixel 1080P USB webcam in low illumination

Input Sample	Eyes Blink Accuracy	Face Detection Accuracy	Drowsiness Detection Accuracy	Emotion Detection Accuracy
1	100%	100%	100%	80%
2	90%	100%	95%	79%
3	100%	95%	90%	80%
4	95%	100%	100%	81%
5	90%	100%	97%	82%
Total	95%	99%	96.4%	80.4%

To calculate and check the accuracy of the model, each volunteer was asked to blink 10 times and become drowsy 5 times during the testing process.

The accuracy for eye blink was calculated by the formula:

Eq.1 **Accuracy** = 1 - |total no. of blinks -no. of blinks detected| / total no. of blinks

The same formula was used for calculating accuracy of drowsiness detection. As we used different cases so we create the Two tables for both the Cases.

1)Table and analysis

2)Table Accuracy of system using Mobile Cam

This project has an 85%-89%curacy rate when tested in different cases. It performs well when it has high illumination or a good light source, but faces errors in low light. It also produces an 87%curate result when tested with glasses.

Literature References

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Summary

In conclusion, the integration of facial recognition and emotion detection models has significant potential for various applications, including driver drowsiness detection, security systems, and human-computer interaction. While there are still some challenges to overcome, such as ensuring privacy and avoiding bias in the training data, the integration of facial recognition and emotion detection models has the potential to revolutionize many fields and improve the quality of life for individuals. Overall, this technology represents a significant advancement in the field of computer vision and has exciting potential for future development and applications.

Future Work

1)Real time monitoring

2)Driver identification

3)Multi model sensing

4)Machine learning based systems

5)Integration with Autonomous vehicles

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