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Driver Drowsiness Detection System using CNN

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Abstract

Driving on highways is an activity that countless people undertake every day, including taxi drivers, bus drivers, and long- distance travelers. However, lack of sleep is a common issue among these drivers, and can lead to dangerous driving situations. In fact, a driver who is feeling drowsy poses a greater risk on the road than someone who is driving too fast. To tackle this problem, machine learning techniques have been utilized to analyze the sate of driver and improve road safety. Specifically, an application has been developed that uses the Region of Interest (ROI) principle to determine if the driver's eyes are closed or opened. The actual purpose of this program is to detect micro sleep and tiredness in drivers using neural network approaches. By detecting facial landmarks on the model through the camera and utilizing Convolutional Neural Networks, the driver's drowsiness can be classified. This proposed model is helpful to create a highly accurate real-time driver sleepiness detection system that is easy to operate.

Keywords: Facial Opencv , Drowsiness Detection, Convolutional Neural Networks Model, Tensor Flow, Keras, Alarm System.

INTRODUCTION

The driver drowsiness detection system plays a critical role in preventing accidents in both personal and commercial vehicles. It is designed to detect early signs of drowsiness before the driver becomes completely inattentive and to alert the driver that they may not be able to operate the vehicle safely. However, this system cannot guarantee that the driver will be fully awakened or that an accident will be avoided, but it can be a useful tool to improve driver safety, especially for long-haul truck drivers, nighttime drivers, and those driving long distances alone or suffering from sleep deprivation. The system has the ability to monitor a driver's actions while driving, examining the maneuvers of the vehicle, which is a crucial task in enhancing driving safety. To prevent accidents caused by driver fatigue, it is important to take steps to ensure that drivers get enough rest before driving. This includes getting enough sleep and avoiding driving during times when tired.

Drowsy driving can be especially dangerous as it can lead to severe injuries and fatalities, and is more likely to occur in sleep- deprived individuals. One of the factors that can lead to accidents on the road is driver fatigue resulting from sleep disorders. The proposed solution in this thesis aims to detect drowsiness in drivers non-intrusively by alerting them, thus preventing accidents and improving safety on the roads. As such, it is crucial that we raise awareness about the dangers of drowsy driving and promote the use of driver drowsiness detection systems. These systems can help alert drivers when they are getting tired and need to take a break or pull over. By taking steps to address drowsy driving, we can help prevent accidents and keep our roads safe for everyone.

LITERATURE REVIEW

Experts have observed that drivers who fail to take breaks while driving are at a high risk of becoming drowsy. Studies have indicated that accidents are more likely to occur due to drowsy driving than drink-driving. Drowsy people are more likely to be undergo most of the accidents. Drowsy driving can be especially dangerous as it can lead to severe injuries and fatalities, and is more likely to occur in sleep-deprived individuals In case of a warning being issued, the COMMAND navigation system indicates nearby service areas for the driver to take a break. The use of intelligent and interactive technology in cars can greatly improve the safety of drivers and passengers on the road. In this paper, the authors aim to develop a prototype that can notify or resist drivers under unacceptable conditions and provide real-time critical information to rescue services or the owner of the car. One of the factors that can lead to accidents on the road is driver fatigue resulting from sleep disorders. To address this issue, the authors propose a driver drowsiness driver drowsiness detection systems can help alert drivers when they are getting tired and need to take a break or pull over. The proposed system uses sensors, such as eye blink sensors, to find whether a driver is drowsy. If the driver is found to be sleepy, a buzzer will sound to alert the driver, and if no action is taken, the system will turn off the ignition of the vehicle to prevent any accidents.

The idea of the project is to develop an advanced driver safety system that continuously examines eyes of the driver to find the signs of drowsiness. A camera has been used by the system to detect small naps or tiny sleeps, which normally lasts up to 2 to 3 seconds and can be a indicator to fatigue. As when these micro sleeps are detected, the system can warn the driver in a timely manner and reduce the speed of the vehicle to prevent accidents. The project involves developing hardware that uses a controller and algorithms for image processing to process data from camera and then issue warnings in the form of an alarm. The system is designed to improve driver safety on the roads and prevent accidents due to the drowsiness.

Driver drowsiness is major contributor to traffic accidents, making it a significant issue for highway safety. If drivers could be alerted before they reach a point of severe drowsiness, many accidents could potentially be avoided. There are two types of drowsiness detection methods - intrusive and non-intrusive. Non-intrusive methods, which measure driving behavior and sometimes eye features, are considered the best option for real-world driving scenarios. Among these methods, camera-based detection systems are highly effective and can provide timely warnings of driver drowsiness. By utilizing these methods, we can improve road safety and can decrease the risk of accidents due to the drowsiness.

EXISTING WORK

The approach you outlined involves utilizing Haar functions to detect facial attributes like eyes and mouth, performing edge detection to precisely extract the eyes, and utilizing Bezier curves to estimate the extracted regions. The approach is unique in its use of bezier curves for efficient distance extraction and K-means algorithm for pre-classification. Additionally, it is crucial to address driver fatigue and raise awareness about the risks associated with driving while tired. However, the method has limitations in situations where the eyes are closed and can be affected by strong illumination variations.

DATASET AND FEATURES

The dataset has of 77x77 pixel grayscale eyes images. They are automatically detected whether that the eye was closed or opened or centered and occupies about the same space in each of the described images.

The task is for recognizing each eye based on the eye position that was shown in the picture into one of categories whether opened or closed. The set used for training consists of around 58,000 pictures and the public test set consists of 4,000 pictures.

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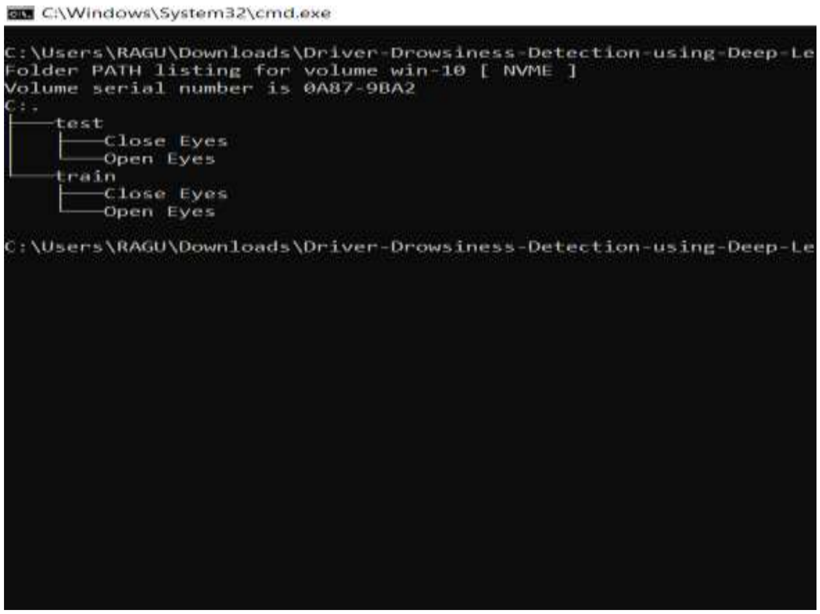

Fig [1]: Datasets used are considered from MRL Eye Dataset.

PROPOSED WORK

CNNs are designed to automatically and adaptively learn spatial hierarchies of features from raw image pixels. CNNs consist of several layers, including convolutional layers, pooling layers, and fully connected layers. The pooling layers down sample the feature maps to reduce their spatial dimensions, while the fully connected layers use the extracted features to make predictions about the input image. The output of these layers is then fed through fully connected layers that perform the actual classification. In the context of drowsiness detection, CNNs can be trained on large datasets of labeled images of sleepy and alert drivers.

By analyzing the patterns and features that are characteristic of each state, the network can learn to accurately classify new images as either drowsy or alert. However, it still requires significant computational power and a large dataset for training.

The proposed method for drowsy driver detection using convolutional neural networks and Viola-Jones Haar-like features involves extracting frames from a video and feeding them into a face detector. The trained classifier is then used to classify drowsy or non-drowsy faces among all the frames. The binary signal for each frame is then used to determine the state of the driver. To issue an alert signal to the driver, at least 30 of 50 frames has to be finalized as drowsy, and a buffer of 50 recent outputs of the frames is maintained. A alerting alarm sound is then sent to the driver as a sign of warning. This method provides a non- intrusive vision-based approach for drowsy driver detection, which can help prevent accidents caused by driver fatigue.

METHODOLOGY AND IMPLEMENTATION

Convolutional Neural Network:

One of the key advantages of CNNs is their ability to automatically learn and extract useful features from images, without the need for manual feature engineering. This makes CNNs highly effective at recognizing patterns in images and achieving high accuracy on a variety of computer vision tasks .They are designed to automatically detect patterns and features in visual data such as images and videos, through a process of convolution, pooling and non-linear activation functions. CNNs work by learnable filters (also called kernels or convolutional filters) to the input image, creating feature maps that highlight specific visual patterns. However, these feature maps can be quite large, which can make training and inference computationally expensive. To address this, the feature maps are often down sampled or pooled to decrease the spatial dimensionality of the data while preserving the most important features. They are highly flexible and can be customized for a specific task by adjusting the number of layers, filter size, pooling size, and other hyper parameters.

Transfer Learning:

This method is a powerful technique that has revolutionized the field of computer vision. It involves using pre-trained models that have been trained on large datasets to solve new, similar tasks. By using pre-trained models, transfer learning can significantly reduce the amount of time and resources needed to train a model for a new task, while still achieving high accuracy.

Additionally, transfer learning allows researchers and developers to focus on the specific problem they are trying to solve without having to worry about training a model from scratch or collecting and annotating large amounts of data. Overall, transfer learning has become an essential tool for computer vision applications, enabling faster and more accurate model development with less data and time.

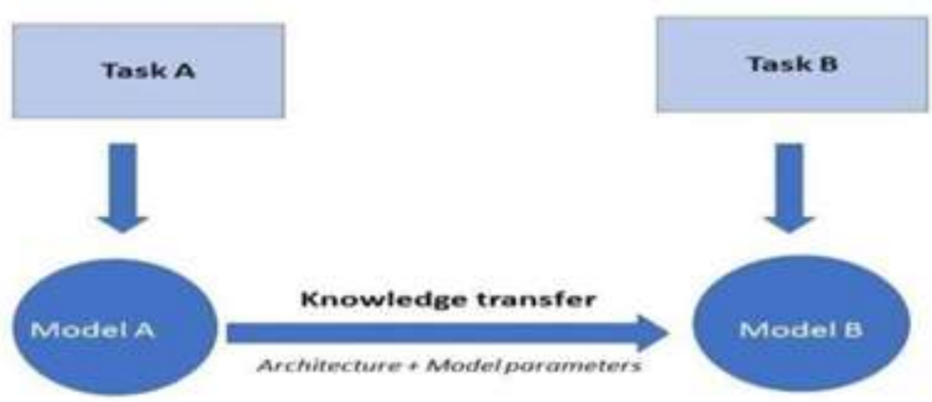

Fig [2]: Transfer Learning

Convolutional Neural Network:
CNNs have become an important tool for advancing computer vision and image analysis, and are widely used in a variety of fields including autonomous vehicles, medical imaging, and surveillance systems.

The Following are the layers in the CNN

- Convolutional Layer
- ReLU Layer
- Pooling Layer
- Fully connected Layer

Convolutional Layer:
In a convolutional layer, the image is convolved with a set of learnable filters (also called kernels) to produce feature map sets. These filters help to extract specific features from the image, such as curves, textures, and patterns. The filter size, as well as the number of filters used, can be adjusted to change the number and type of features extracted. The output feature maps are then passed to the next layer for further processing.

This layer requires three components:

- Input data
- Filter
- Feature map

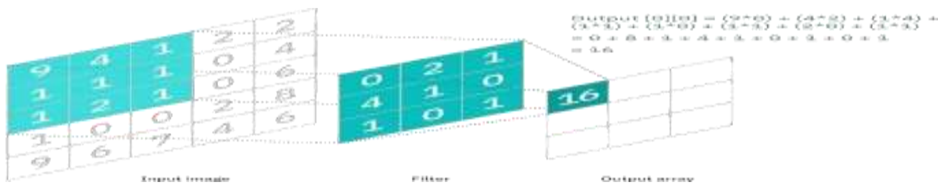

Fig [3]: Convolutional Layer

ReLU Layer:

ReLU refers to Rectified Linear Unit. This layer ensures that every negative value in the feature map is replaced with zero.

ReLU Function: f(y)=max(0,y)

- On the feature map it operates element wise.
- It gives the output of the rectified feature map.

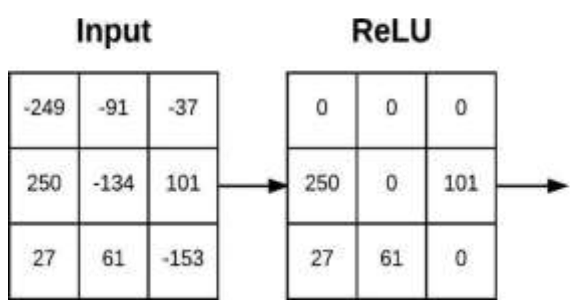

Fig [4]: ReLU Layer

Pooling Layer:

Pooling layer usually comes after convolutional layer. Pooling layer can be used to decrease the feature map size and to reduce the cost of computation.
Pooling Techniques mainly are of three different Types, they are:
Max Pooling Min Pooling Average Pooling

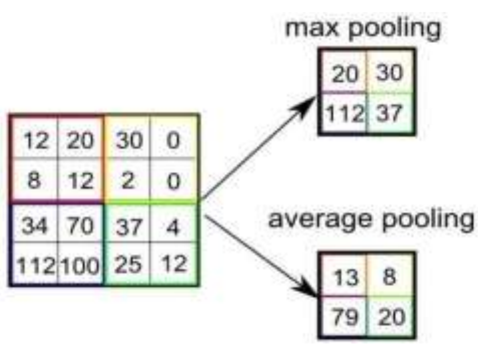

Fig [4]: Pooling Layer

Fully Connected Layer:

These layers are often used in the final stage of a neural network for classification tasks. They take the results of the previous convolutional and pooling layers, which extract the features from the images given as input, and convert it into a form suitable for classification. Each neuron in the fully connected layer represents a possible output class, and the neuron with the highest activation value represents the predicted class for the input image. In the case of facial expression recognition, the fully connected layer would have seven neurons, each corresponding to one of the seven possible expressions.

RESULTS

CNN model is set to 50 epochs and when trained gives accuracy 85%. The designed CNN model was able to recognize the drowsiness of the person based on his eye moment and can able to warn him.

User Interface Results

These user interface results are considered to show the final output for the following paper work. This helps the user to interact easily without any background knowledge how the code works. The user interface results are displayed in the below figures Fig [5] and [6].

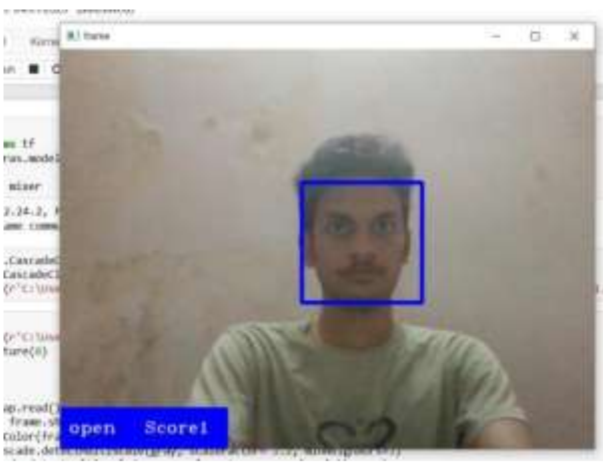

Fig [5]: When the user is normal and active

Fig [6]: when the user is drowsy

CONCLUSION

It sounds like the technology has the potential to greatly improve road safety by alerting drivers who may be at risk of falling asleep at the wheel. An accuracy rate of 83.2% is impressive for real-time predictions, and the ability to measure tiredness through yawning is an interesting addition. This technology could also have applications beyond driving, such as in industries where workers need to stay alert for safety reasons.

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