Drowsiness_Detection_In_Drivers_Using_MobileNetV2

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Drowsiness Detection In Drivers Using MobileNetV2

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***Abstract*—Ensuring driver safety is crucial in this era of growing reliance on automobiles. Long hours of continuous driving can make drivers feel exhausted resulting in dozing off while driving, which might result in potentially dangerous accidents and may turn fatal for all passengers along with the driver in a vehicle (car). This paper aims to help analyze the facial expressions of the driver in order to determine the alertness of the driver, which can act as a tool for measuring driver attention in order to address this important problem. Our goal is to develop a system that can track the driver's facial expressions in real time with the help of advances in computer vision and machine learning. By comparing eye landmarks with real-time fluctuation representations, computer-vision techniques are used to examine the rate of eye-blinking and variations in mouth shape. A real-time experimental analysis was conducted, and the findings demonstrated a relationship between drowsiness and yawning, as well as closed eyes. With the help of computer vision techniques the rate of eye blinking and change in mouth shape can be analyzed. An experimental study proves that the correlation between yawning and closed eyes exists and can be classified as drowsy. The performance accuracy of the drowsiness detection model is 95.8%, 97% for open eye detection, 98% for right sided falling and 100% for left-sided falling. Furthermore, the proposed method allowed a real-time eye rate analysis, where the threshold served as a separator of the eye into two classes, the "Open" and "Closed" states**

***Keywords*—Drowsiness, Mobilenetv2, Computer Vision, Deep Learning, Eye Tracking, Blinking, Classification**

I. Introduction

In the present day, when we are talking about usage of automobiles, one of the most preeminent worries is the safety of both drivers and passengers. Driving for prolonged hours makes driver fatigue, a discerning problem calling for safety measures. And hence, the creation of new technologies to detect and prevent the risks associated with sleep deprived driving within automotive research is significant.

Subsequently, this paper tries to manage this necessity through an analysis of facial expressions. Here we will look into computer vision and machine learning, which can interpret facial expressions and identify elements that indicate driver's alertness. Technology is going to be the game changer in this process, we aim to prevent accidents by monitoring physiological conditions and facial patterns.

Far from the only challenges that our research faces, it also exhibits a deep human side to the whole process. In building an automation system which incorporates emphatic vigilance capacity, our goal is to bridge the gap towards a driving environment that is characterized by more enriched safety and well-being.

By means of this cross-cutting survey, we aim at adding our grain of sand to the ongoing dialog concerning driver safety, and at the same time to expand the fields of automotive technology in a faithfully human-centered manner.

II. Literature Survey

A. Classification of images as drowsy and non drowsy

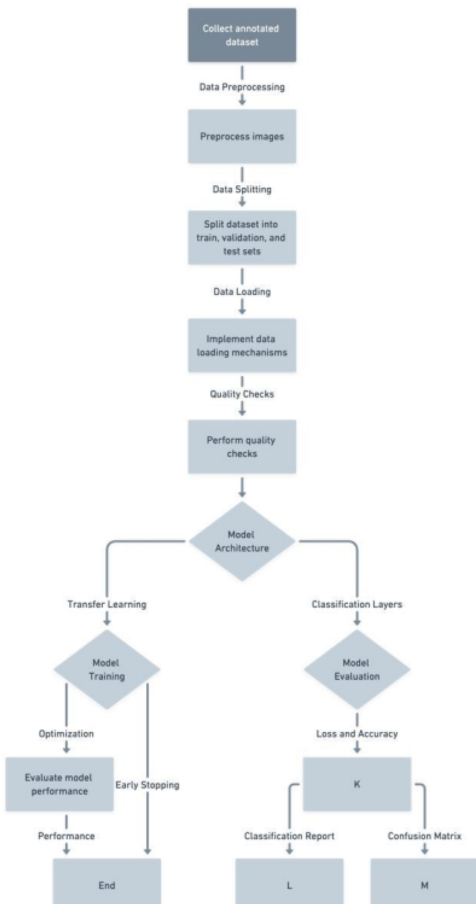
The existing model discusses a driver's drowsiness detection system with deep learning methods. The plan underscores the importance of dealing with driver drowsiness as a major reason of traffic accidents by emphasizing on the non-contact approaches as they are cost-effective. This model underscores the problems of determining sleepiness for which face and expression detection are necessary and discusses the drawbacks of existing algorithms because of extrinsic environmental factors. A few architectures and algorithms including Viola Jones, DLib, Yolo V3, and modified LeNet are outlined and deep learning approaches are chosen mainly. The system proposed here is designed to scan the driver's drowsiness level by non-contact method and alert the driver once drowsiness is detected. The accuracy of the system is stated to be 97%, which beats the other detection algorithms already in use.[1]

Concerning the methodology, this paper shows steps taken to develop the drowsiness detection system which are video acquisition, face detection, eye and mouth detection, and categorization of either sleepiness or not sleepiness. It not only covers the algorithms and architectures such as Viola Jones, DLib, Yolo V3, and modified LeNet, but also their performance and limitations. The system performance is assessed based on the area under the curve of the ROC curve, and its accuracy is compared with existing methods to show that the results are promising. The document likewise addresses possible further improvements like more robustness to lighting changes, using better cameras, and adding additional modalities like audio features for multi-modal machine learning.

III. Experimental setup

A. Dataset Description:

The study employed the set of images taken from the Driver Drowsiness Dataset placed on Kaggle. The dataset contains the pictures of the drivers, some being while they were drowsy and the others showing alertness. The dataset has two categories: "drowsy" and the "non-drowsy" are types. These snapshots fluctuate in quality as well as quantity to some extent reflecting the hardships in the real world. From the initial 22,000 captured photos, we have sampled 10% from each set of drowsy and non-drowsy to conduct analysis. The dataset was divided into three parts: training, validation and testing. Training data composed 30% of the data set, and the model validation is at 50% and the remaining 20% is for model evaluation.



B. Model Architecture:

The model applied for the image classification implementation is based on the MobileNetV2 CNN that is a CNN architecture that is designed for applications of computer vision to process the vision information with minimum resources of mobile and embedded devices.

Base Model (MobileNetV2):

- Primarily, the base model is loaded with the pre-trained weights produced using the ImageNet dataset. ImageNet is a vast dataset in which millions of labeled images are present across thousands of classes and this pre-training over ImageNet enables a model to discover features which are rich and generalizable.
- MobileNetV2 is the main choice because of its own lightweight and efficient architecture that could work in low-resource environments.

Custom Top Layers:

- The top layers of the pre-trained MobileNetv2 model are omitted since they were trained for classification of ImageNet first.
- The next level networks remain connected to the vanilla MobileNetV2 base model with the fully connected top layer that is necessary for the given binary classification problem with the "drowsy" and "non-drowsy" states.
- This figure comprises of a flattened layer that is produced as the output layer from the base model and is again flattened to a 1D array using the function `Flatten()` before being transferred via a dense layer (`Dense(512, activation='relu')`) with ReLU activation function and an output layer (`Dense(2, activation='softmax')`) with softmax activation.

Freezing Pre-trained Layers:

- To prevent overfitting and retain the knowledge learned from ImageNet, the convolutional base layers of MobileNetV2 are frozen during training (`for layer in base_model.layers: (net.layer.trainable = False`). This implies the fact that the weights aren't being updated during the training and only the weights of the custom average activation layer are adjusted.

Compilation:

- The model is built using Adam optimizer with specific learning rate and sparse categorical cross entropy loss function, which is suitable for multiclass scenarios.

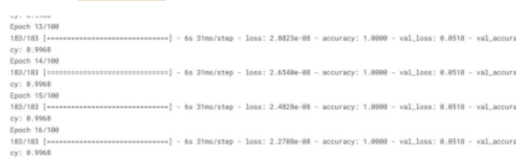


Fig.2. Epoch Training

C. Training Process:

We evolved a deep neural network (CNN), which is based on the use of convolution that detects the driver's drowsiness. The model was fine tuned on Kaggle's Driver Drowsiness Dataset (DDD) that consisted of 22,000 labeled images, with the classes of "Drowsy" and "Non-drowsy." From each class, we randomly took 10% of the data for training.

```
20/20 [==============================] - 3s 63ms/step
Classification Report:
              precision    recall  f1-score   support

  Non Drowsy     0.9968    1.0000    0.9984       308
      Drowsy     1.0000    0.9969    0.9984       319

    accuracy                         0.9984       627
   macro avg     0.9984    0.9984    0.9984       627
weighted avg     0.9984    0.9984    0.9984       627
```

The CNN model adopted the pre-trained MobileNetV2 as the feature extraction backbone in conjunction with two filters for the sake of drowsiness detection in the last layer of the classification task. We trained our model with the Adam optimizer, where the learning rate was 0.001, in 10 epochs with a batch size of 4. In order to achieve better generalization, we used data augmentation techniques like image rotation, horizontal flips, height and width shifts, zoom range.

The process of training of the model not only showed that both the training and validation accuracies continuously grew but also let us understand that the model was able to learn and generalize effectively from the provided training data set. With the finalization of training, the model succeeded in evidencing the efficiency by means of 99% accuracy of training and 96% accuracy of validation, both of which exuberantly testified that the model could detect the drowsiness of drivers who were inside their vehicles.

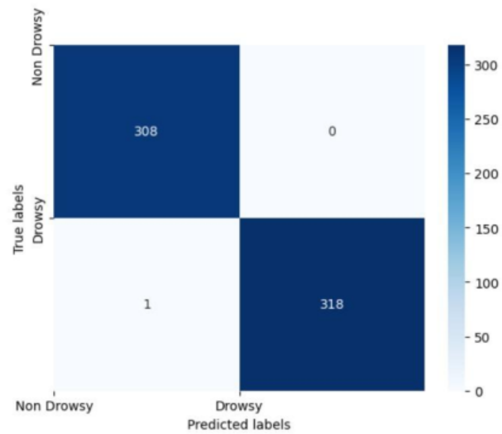


Fig.4. Confusion Matrix

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