Leveraging Transfer Learning for Driver Drowsiness Detection

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Abstract. The annihilation of one's life due to road accidents has been increasing due to human fallacy. Various awareness programs have been commemorated to eradicate portent possibilities over crust but the graph stays exponential. In this paper, we've tried to incorporate a lightweight system for scrutinizing and conceding Driver's Drowsiness state using eyes as our subject, with Transfer Learning approach. Here, we have subsumed the MobileNet model over MRL Eye Dataset, stratifying it into 02 classes as Open and Closed eyes. In our study, we achieved an accuracy of more than 97% and cocksure our efficacy for creating an insubstantial as well as an exemplary model for Driver Drowsiness Detection.

Keywords: Driver Drowsiness Detection (DDD); Transfer Learning; MobileNet; MRL Eye Dataset.

1 Introduction

As claimed by the World Health Organization (WHO), traffic accidents are one of the top ten causes of death worldwide. According to the National Sleep Foundation, about half the adult drivers of the U.S. admit their presence behind the wheels while feeling drowsy. According to numbers, around 20% divulge to fall asleep while driving at some point over a year and 40% avow that it happened no less than once in their lifetime. These staggering figures show how pervasive drowsy driving is.

As a result, there has to be an elucidation to inhibit accidents caused by drowsiness. Although there have been many studies to develop a proficient technology to detect a driver's drowsiness state based upon yawning, nodding, etc. but these phenomena don't give the certitude when compared to varied humanistic behavior. Although Driver's Heart Rate (HR), respiration rate, rapid eye movements, and head movements are some anatomical aspects that have been looked upon, it doesn't comply with the tranquility in this domain. Physiological sensors which have to be worn by the driver and Biosensors such as Single-Channel Electroencephalogram (EEG), Portable Glasses for Electrooculography (EOG), Photoplethysmography (PPG) Hand-Bands are some efficient solutions but this involves a physical entity over a human body and relying solely upon it would result into fatal and also the incorporation of such set-up would be arid.

As a result, there needs to be a solution that would elevate the process of DDD with trivial efforts and be a pre-eminent outlook. In this paper, we have tried to assimilate the most optimal and lightweight solution by focusing upon the eyes of the human body. Eyes when closed for an unusual time can instantiate the driver's drowsy state. Many pieces of research used Deep Learning from scratch which wouldn't turn out to be coherent and thus, to make our model feathery and fast we integrated Transfer Learning where there are Deep Learning Networks pre-trained over 1000 classes on ImageNet. More specifically we used the MobileNet model as it's comparatively frothy and accurate. A real-time eyes state was captured using the Computer Vision methodology. The result was highly potent and accuracy was astonishing in corporeal time. Also, keeping a pukka outlook for an embedded system, we generated a siren when eyes were kept closed for an unconventional time. This structure would emphasize a more authentic and humanly solution to prevent and minimize traffic accidents caused due to the driver's drowsiness state. It gave better results when compared to hefty objects embedded over the body resulting in a petty yet effective real-time solution for DDD.

2 Literature Survey

Effective studies for the prevention of life due to misconstruing have been carried out over varied technologies and all related anatomical aspects. Compression of Deep Neural Network Model over an embedded system has been proposed beholding an accuracy of just 89.5% on 3-class classification and speed of 14.9 fps (Frames Per Second) on Jetson TKI **[1].** Moving towards advancement, Heart-Rate Variability (HRV) based drowsiness detection system is formulated with validating it over Electroencephalography (EEG) based scoring but it needs drivers to embed electrodes on their skin while driving **[2]**.

Furthermore, Driver's Drowsiness state was detected based upon Respiratory Signal Analysis resulting in specificity and sensitivity of more than 90% **[5]**. Functional near-infrared spectroscopy (fNIRS) has also been inculcated to enhance DDD using Deep Learning Model such as Convolutional Neural Network (CNN) **[8]**. A real-time DDD algorithm has also been engulfed with Individual differences consideration. This architecture proposes an accuracy of 94.80% with 640*480 resolution images at over 20 fps **[9]**. Advanced Driver Assistance System (ADAS) has been proposed using Facial Landmarks with a precision of 87% **[11]**. Also, there is a proposed algorithm that uses an AdaBoost classifier based on Modified Census Transform features. It uses Regressing Local Binary Features for facial landmark detection **[12]**. DDD through yawn identification based on Depth Information and Active Contour Model has also been formulated with an accuracy of 95% **[14]**.

Behavioral measures and Machine Learning techniques such as Hidden Markov Models have been interpreted for Driver Drowsiness Detection **[16]**. Additionally, A Smart Driver Drowsiness Detection (SDDD) Model has been serialized over Analytic Hierarchy Process (AHP) **[18]**. Moreover, A comprehensive methodology has been devised combining Multi-Modal information for drowsiness level detection with Root Mean Squared Error (RMSE) of 0.620 **[20]**. These results prove a wide spectrum of possibilities for DDD and thereby preventing contretemps and encompass all domains of survival. All these methods have huge embedded systems and are infatuated in real-time. While driving, incorporating such entities for safety wouldn't be quintessential and thus our model represents a solution that would give accuracy and represent more authentic explication.

3 Proposed Approach for Driver Drowsiness Detection

In a plethora of methodologies, creating the most efficient system has led to variability in bodily attributes and their singularity. But to make a system more crisp and less fuzzy a trivial yet enhanced system has to be generated discarding tangible aspects affecting a human body. A driver's drowsiness state can be identified by unusual movements of its eyes and thus a system can be proposed. The same approach which is superficial has been put forward analyzing its impact live.

A. Dataset used: MRL Eyes Dataset is an impeccable dataset of human eyes images. It inculcates infrared images in low and high resolution captured in varied lighting conditions and through different devices. It procures images of the eyes of 37 different persons (33 Men, 4 Women) with and without spectacles.

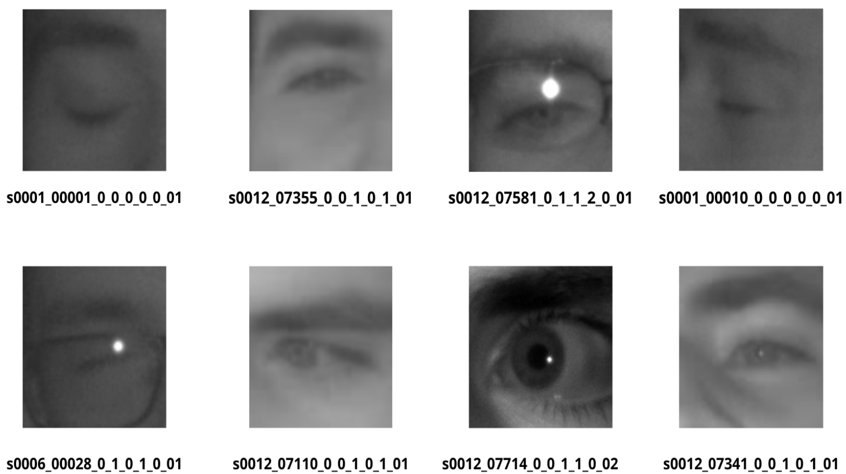

Fig. 3.1. Representation of Annotated Images of MRL Eyes Dataset

B. Transfer Learning: Transfer Learning is a Machine Learning approach where a model codified for a task is reutilized as the initial point for a model on another task. It varies from the traditional ML method as it uses pre-trained models to stimulate the development process on a fresh problem.
One of the benefits of Transfer Learning is, it can deteriorate the time taken to formulate and train a model. This helps to boost up the model's training and thereby accelerate the results.
Let's have a glimpse at Transfer Learning Approach:

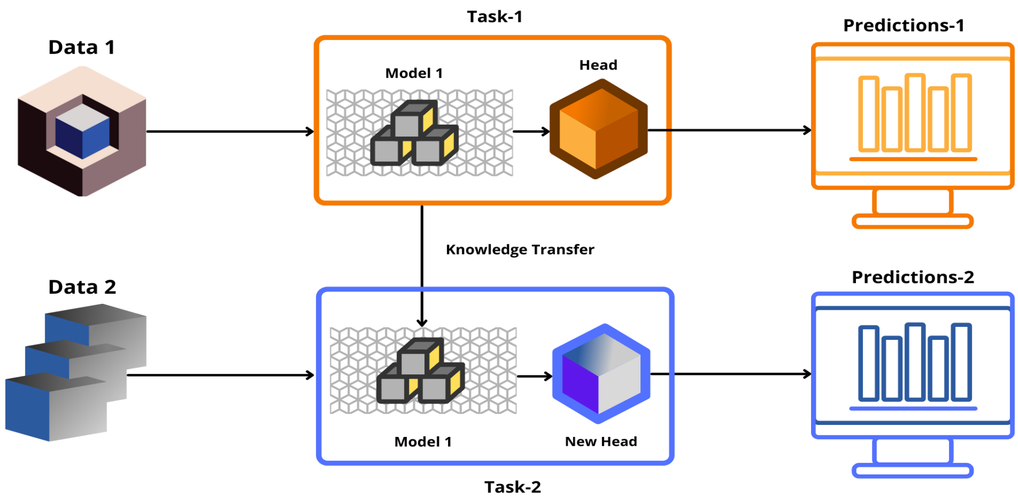

Fig. 3.2. Transfer Learning

C. MobileNet Architecture: MobileNet is coherent and as the name suggests "Mobile" CNN architecture that is used in real-world phenomena. It radically uses depth-wise separable convolutions instead of standard convolutions used in prior structures to build flimsy models. MobileNets commemorates two avant-garde global hyperparameters (width multiplier and resolution multiplier) for pace and low size depending on prerequisites.

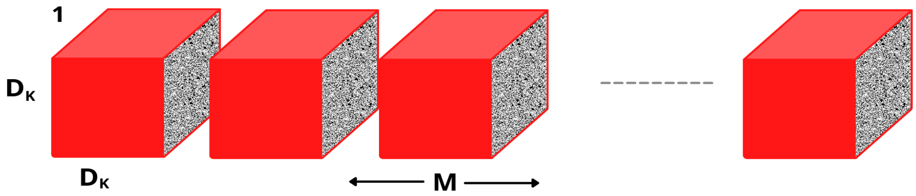

Fig. 3.3. Depth-wise Convolutional Filters

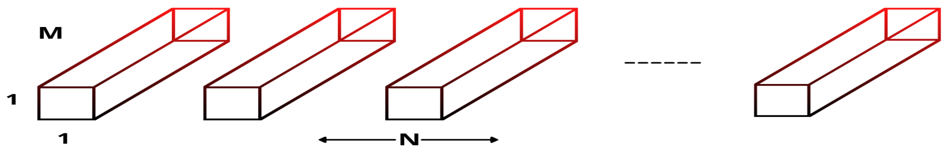

Fig. 3.4. 1x1 Convolutional Filters called - Pointwise Convolution

MobileNets are composed of Depth-wise Separable Convolution Layers. Each depth-wise separable convolution layer comprises depth-wise convolution and a pointwise convolution. Collating both it has 28 layers. This architecture consists of 4.2 million parameters which can be altered by modulating the width multiplier hyperparameter aptly.

- **Width Multiplier**: It's a global hyperparameter used to contrive smaller and less computationally expensive models. It is denoted by α. Its values lie between 0 and 1.
- **Resolution Multiplier**: Another parameter of MobileNets is Resolution Multiplier. It's denoted by ρ. This hyperparameter is used to dwindle the resolution of the input image and this eventually sinks the input to every layer by the same factor.

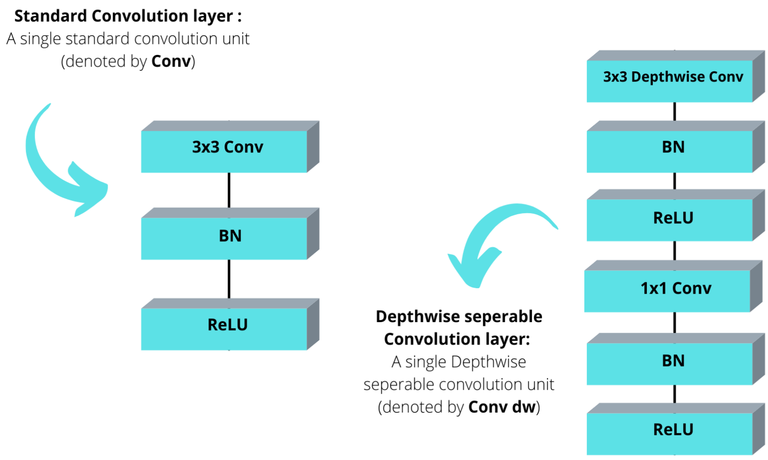

Fig. 3.5. Comparison between Standard and Depth-wise Separable Convolutional Layer

D. Methodology and Implementation:

Now, it's time to implement our architecture and method over MRL Eye Dataset. There are two classes for eyes – Open Eyes and Closed Eyes. Visualization of our model is specified below:

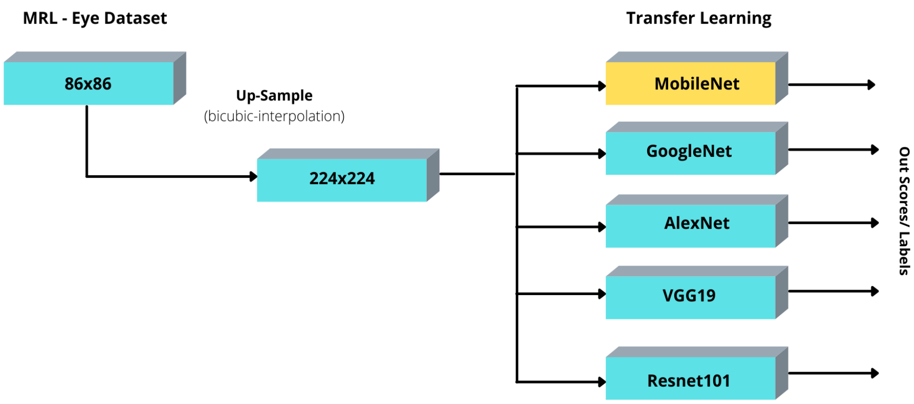

Fig. 3.6. Proposed Architecture

Within transfer learning, there are various Deep Learning models which are pre-trained over 1000 classes on ImageNet such as MobileNetV2, ResNet101, VGG, AlexNet, etc. which can be used for similar classification problems. We have used MobileNet in our approach since it's lightweight and fast and shows accurate results. Images have been resized to 224x224 as the dataset consists of varied size images, and then normalized further to prevent overfitting. Moreover, reading all the images and converting them into an array for Data and Labels. Now, the Deep Learning Model (MobileNet) is introduced for Training and Learning. Variables have been designated for Binary Classification and the Network is analyzed through predictions.

Note: While using Transfer Learning the domain of the problem should remain the same i.e., if MobileNet is pre-trained over a Classification problem then it can be only used over other Classification problems.

Now, the Network is tested upon unknown images, and thus for Closed Eyes the value moves towards 0 and for Open Eyes, the value moves towards 1. Furthermore, to test our model in real-time a sound alert has been consolidated and when the driver's eyes remain closed for a second, a siren sound is heard.
The whole methodology can be subsumed as:

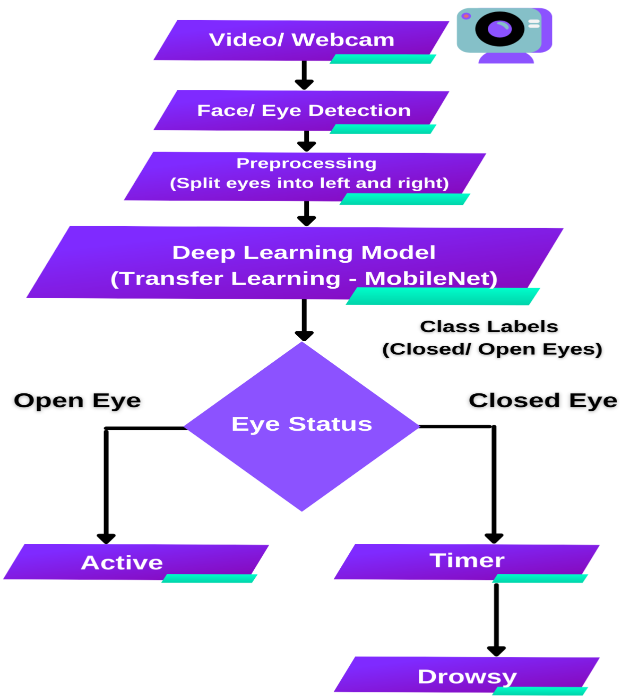

Fig. 3.7. Model Flowchart

E. Results: The whole model has been facilitated and the eyes state has been detected with glasses and without glasses to ensure the model's efficacy. The model got an accuracy of 98.45% over 84,000 instances, giving a liable and effective stratagem for inhibiting accidents due to drowsiness. The real-time demonstration has been envisioned in Fig. 3.8.

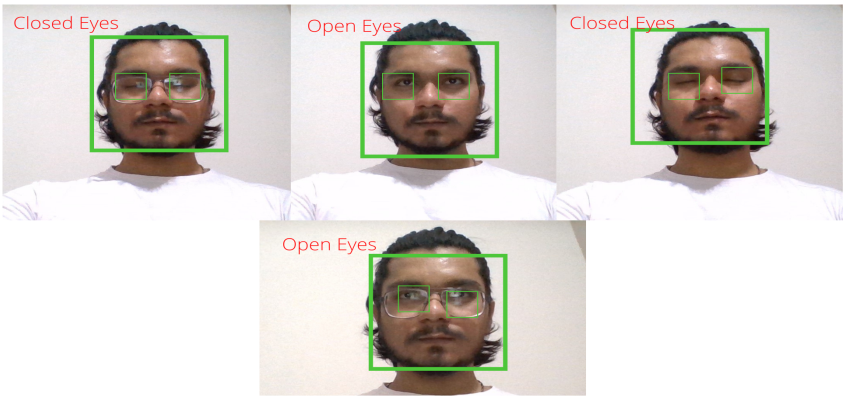

Fig. 3.8. Realtime Video Demonstration

Furthermore, the plot shows the stratifying results:

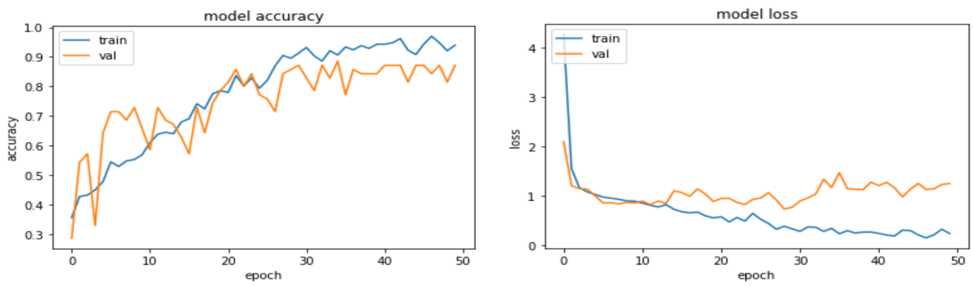

Fig. 3.9. Model Accuracy and Loss Result

Table - 3.1. Model's Accuracy Result

Accuracy	Percentage
1. Training Accuracy	99.45%
2. Validation Accuracy	94.75%
3. Test Accuracy	98.45%

4 Conclusion and Future Scope

The model proposed gives an efficient and viable solution for Driver's Drowsiness Detection and thereby prohibiting road accidents. The other methods are effective but when implemented in real-time can contemplate monetary outlook for masses as well as physical liability such as HRV, EOG, PPG, etc. Thus, a lightweight embedded system can be thought of as an authentic pathway for successful integration of this method i.e., eye state detection with an alarm over vehicles. Increased rate of fatality can be prevented and a veritable system may be accessible by refuting unnecessary approaches. Different Deep Learning models can be used and the number of Classes can be increased to make the system more accurate and precise using Transfer Learning, thus making trivial but impactful modus operandi for the masses. Fig. 4.1. demonstrates the potency of the proposed architecture.

Table - 4.1. Comparative study between different studies

Research Types	Research Results
1. Heart – Rate Variability Test with EEG	80% - 90%
2. DDD based on Respiratory Signal Analysis	96.6%
3. Using MobileNet Architecture (This Paper)	98.45%

5 Sources of Figures

The images used in this paper are self-created referencing subsumed algorithms and its architecture conceptually. The authors sustain no obligation for its educational use.

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