Survey on Driver Drowsiness Detection Systems in Advanced Driver Assistance Systems

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Abstract— As per the National Highway Traffic Safety Admin- istration (NHTSA) approximately every year close to one lakh road accidents occur because of driver drowsiness. In the year 2017 alone around 1,47,000 people were killed in accidents on the road in India. Each year, millions of people lose their life due to road crashes caused by driver drowsiness. In order to tackle this, people around the world created solutions withthe help of different aspects of technology. There are two main measures that are crucial in deciding the degree of drowsiness that the driver is undergoing. Physiological measures are contingent on the impact of the environment on the driver and its affect on various health related signals like ECG and EEG. Behavioural measures largely focus on the driver's facialfeatures and its impact on the vehicle. This paper presents a thorough survey on existing methodologies that are builtusing these features as their foundation and showcases which methodology slightly outweighs the others and its future scope.

Indexed Terms— Behavioural Measures, Physiological Measures, ADAS, Deep learning, CNN, ECG/EGG

I. INTRODUCTION

With an increase in the number of vehicles on the road, there is also an increase in the number of vulnerabilities faced by the driver. To understand what possibilities can be preventedin advance, one needs to understand all the possible causes of a traffic accident. One of the most common problemsthat affect drivers while driving is drowsiness, especially if the drive is very long. One way to reduce accidents caused by driver fatigue is to detect driver fatigue early and issuean alarm promptly. As per the records of NHTSA, around 1,000 traffic accidents occur each year in the United States due to driver drowsiness. NHTSA reported that 72,000 road accidents, 800 deaths, and 44,000 injuries were due to driverfatigue. In 2017, about 1.47,000 people were killed in road accidents in India alone.[1][2]

According to the authors of "Deep CNN: A Machine Learning Approach for Driver Drowsiness Detection Based on Eye State" While driving a vehicle, the driver may experience different stages of drowsiness, some of these stages include yawning frequently, inability to open one's eyes sudden decrease in the speed of the vehicle etc. To measure the level of drowsiness accurately, various detectiontechniques are used. These measures include, behavioural, physiological and vehicle-based measures. [1][2]

Based on the movements of the steering wheel and the brake patterns, vehicle-based measures detect drowsiness. Thesemethods are contingent on skills of the driver as well asthe pattern of the road on which the driver is driving. Thebehavioural metrics take into account the facial features andany change in those features over the course of the drive. Asmart camera is utilized here to comprehend and process all of this information. As compared to vehicle-based measures and physiological-based measures, behavioral measure is the most accurate way to measure driver drowsiness. Yawning frequently, slowing the vehicle down frequently, swingingthe head forward are all considered as signs of drowsiness.Another excellent parameter that is used to detect driverdrowsiness is the amount of time the driver has their eyesclosed. A lot of facial features like dropping of the jaw,movement of the lips for yawning, are being used in up-coming research for detecting drowsiness in drivers.[2][3] Face recognition technology is divided into image based and feature based technology. In the image based approach, neu-ral networks based on statistics and subspace linear methods are implemented. Image based approach also uses different eye-detection algorithms to extract important features thataid in predicting the degree of drowsiness .

One can adjust the difference in contrast between facial images by executing histogram-equalization. Extraction of features is implemented in the input image in the eye region.Methods to extract features from the generated image are primarily of two types, appearance based and geometry based methods.

In appearance based methods, the image of the driver'sface is taken in and modules are run to see if the driver's eyes are open or shut. The image can only fall into these three categories. However, in geometry based approaches, the accuracy of the prediction is increased as now the modelcan predict if the eyes are partially open as well, this is alsoa crucial factor in indicating the level of drowsiness.[3][4]

The most commonly used theoretically rigorous approachesinclude the analysis of electro biological signals such aselectroencephalograms (EEGs) and eye-like facial featuresbased on the rate at which the eyes are closing during a time window (PERCLOS) that is fixed over a period oftime. The PERCLOS approach has proven to be more than90 percent accurate in detecting performance degradation atboundary operations. These numbers show that PERCLOSis more reliable than EEG, blinking, and head position indriver research. In this approach, the idea proposed is touse the eye image of the camera directly without an eyetracking system that is highly expensive. Here,movementsof the eyes are comprehended with the help of a recurrentneural network (RNN) which is used to detect the level of drowsiness. Long Short Term Memory (LSTM) is aclass of recurrent neural networks and has a lot of addi-tional features which make it a lot better and faster. Themethodology used here uses a bunch of LSTMs to trackany movements related to eyes. Over here, two differenttypes of LSTMs were used .1-DLSTM (R-LSTM)was usedas a baseline and a convolutional LSTM (C-LSTM) whichcan use 2D images directly. A 48 x 48 patch around boththe eyes was extracted from 38 drivers who participated inthis driving experiment. Subject's wakefulness was assessedindependently by power spectral analysis of simultaneously recorded multi-channel electroencephalogram (EEG) signals to generate binary markers for wakefulness and drowsiness (baseline). The results have shown the high efficiency of thesystem that was proposed. The accuracy of the R-LSTM-based approach was about 82 percent, and the accuracy ofthe C-LSTM-based approach ranged from 95 to 97 percent.It also shows that the proposed LSTM method is far superiorto the recently published eye-tracking approach.[5][12][7] Another novel approach examines the strong and identifiablepatterns of the HRV or Heart Rate Variability signals cap-tured by the wearable photoplethysmogram (PPG) or elec-trocardiogram (ECG). sensors to detect driver drowsiness.Wearable sensors are highly sensitive to slight movements, so the signal is often noisy. Therefore, it is necessary tofind a good function from the noisy HRV signal that makes a good distinction between sleep and wakefulness. For this purpose, the authors examined three types of recurrenceplots (RP), Cont-RP, ReLUiRP and Bin-RP which were gen- erated by the R-R interval (RRI) produced by the heartbeat.Each of the RPs was used as an input function to a CNN toinvestigate their worthiness for sleepy / awakening catego-rization. In the experiment, the authors used the Microsoft(MS) Band 2 PPG sensor , the Polar H7 harness ECG sensor in a driving environment which was virtual to collect RRIsfor drowsiness and arousal. The results show that ReLU-RP is the very reliable for detecting drowsiness as comparedto the other RPs, regardless of sensor type (ECG or PPG). In particular, the ReLU-RP-based CNN model showed im- mense superiority over the other traditional models that are present, with ECG accuracy of approximately 6-17 percentand PPG accuracy of 4 when classified as sleepy / awake, there was a 14 percent improvement.[12]

With the help of the thorough survey conducted in this paper, one can fully understand the research gaps and areas thatcan be improved in the field of driver drowsiness detection in ADAS.

1.1. Motivation for Research

With the advancement in driving technology, there is alsoa need to improve the safety aspect of driving. As more consumers buy automotive vehicles there is a higher prob- ability of accidents and mishaps. Driver drowsiness is the consequence of many circumstances that any driver comes across on a regular basis. For instance, overnight driving canbe directly correlated to driver drowsiness which can be a potential threat to the driver and the passengers in the vehi- cle. In order to prevent this, many researches and developersaround the world are building advanced driver assistance systems with the feature to detect driver drowsiness.

1.2. Relevance of the research for present/future scenarios

Currently, drivers around the world come from differentlife paths and have different levels of driving experience. However, most of them will experience some drowsinessat some point. With the help of this study, one can clearly understand the different factors that cause drowsiness and the different tools and technologies that can help preventand detect any degree of drowsiness.

II. PRELIMINARIES

2.1 Viola Jones algorithm

Despite being an outdated framework, Viola-Jones is ex- tremely robust and powerful, its application is proven to be very remarkable in facial recognition done in the real world.This particular algorithm takes a huge amount of time to train, however, it can detect faces in real time at a very reliable speed.[1]

Given a grayscle image, the algorithm takes into accountall the small sub regions and detects the face by finding specific patterns and features in every sub region. Images can contain many faces of different sizes, so you need to look at different positions and scales. Viola and Jones used a feature which was similar to hair to recognize faces with this algorithm.[1]

2.2 Convolutional neural networks (CNN)

ConvNet (CNN), is a learning in-depth algorithm, which is used widely in most image processing environments. This algorithm is said to learn the different biases and weights associated with the different elements present inthe embedded image, this segregates the images from each other. The algorithm captures the input image in the formof a pixel value matrix, directly using its length, width, number of channels. The first layer in this network is a

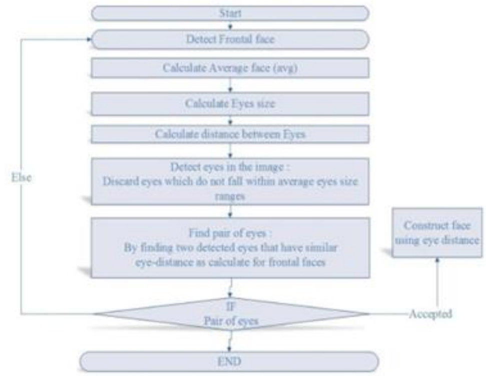

Figure 1. viola-jones face detection algorithm [14]

convolutional layer, the image fed here is the input image. This convolutional layer consists of a bunch of flexible cables, that covers a small area of the input image, that hovers around the image to study the different features thatit contains.[2][8][9]

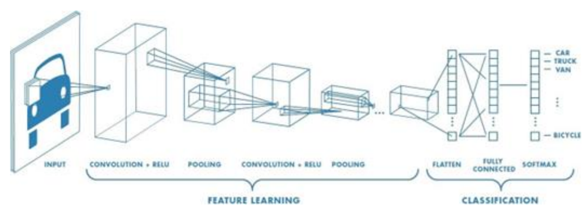

Figure 2. CNN [15]

2.3 AlexNet

In the past, CNN was used for recognition of manual digitalsonly, however, it wasn’t accepted well in all categories of imagery. To further enhance CNN’s ability to learn, this model was brought to the market in 2012, this demonstrated the strong effects of classification methodologies and image recognition. This model has deepened CNN by introducing various parameter enhancement strategies. CNN is made to work by classifying images into different categories, feature-releasing categories have been expanded from 5 (on LeNet) to 7 (on AlexNet). But,the problems such as over-immersionand the disappearance of gradient descents arise, as the depth of the model increases.[2]

2.4 FlowImageNet

FlowImageNet is comprised of eight layers, five convolu- tional layers, and three FC layers.This model consists of the ReLu activation function, this is done to solve the vanishing descent and over fitting problem.[1][2]

2.5 Representation Learning Using Spatio-Temporal Approach

The purpose of this method is to find the rich and discrim- inatory aspect in frames that are consecutive. The videos captured with the help of the front-facing camera on the units of the car display can be differently adjusted, these depend on a variety of car or interior conditions, such as lighting conditions and the car's internal structure. When a driver feels drowsy, the driver's facial features undergo a plethora of changes, and these can be seen as mood swings or changes in movement. Therefore, in order to get the drowsiness of the drivers, the authors considered representa-tions that can define location information (appearance) and temporary information (movement) at the same time. It is not possible to quantify temporary information using only one framework as one framework can contain changes in chronological order. Considering these perceived limitations when the input is an entity that is single, it is important to use different consecutive frames as an input to obtain local and non-permanent information at the same time, in this work, the authors used 3D-DCNN which is used to detect various local and temporary changes in the provision of multiple consecutive frames.[4]

2.6 Electroencephalography (EEG)

The human brain contains billions of neurons, which playa major role in ensuring that the human's external and internal motor systems are regulated. These neurons become carriers and transport information between the brain and the body Recognizing and comprehending mental behavior can be performed by analyzing images and signals generatedin the brain. The behaviour of humans can be thought of in relation to sensory and motor conditions such as lip movements, changes in eye behaviour etc. The regions are correlated to the frequency of a specific signal that helps to better understand the functional behavior of somethingas complex as the human brain. Electroencephalography (EEG) is an effective technique that helps to detect the most common brain symptoms taken in the scalp. These signals are generally classified as alpha, delta, beta, theta, gamma based on frequencies of signals which range between 0.1HZ -1000 Hz[5][12][9]

III. METHODS BASED ON DEEP CNN

3.1 Viola-Jones Algorithm and Deep CNN

- The algorithm helps in detecting faces in an image which is given as an input to the eye detection algorithm implemented by Viola-Jones.
- When the algorithm detects a face, the Viola-Jones eye detection algorithm is used to carve out the eyes from the face image, post this it is provided as input to the CNN.[1]
- A CNN with four convolution layers is used to extract deep features, which are passed to the fully connected layers.
- CNN's layers that use Soft Max help in classifying images into sleepy and awake images.[1][2]

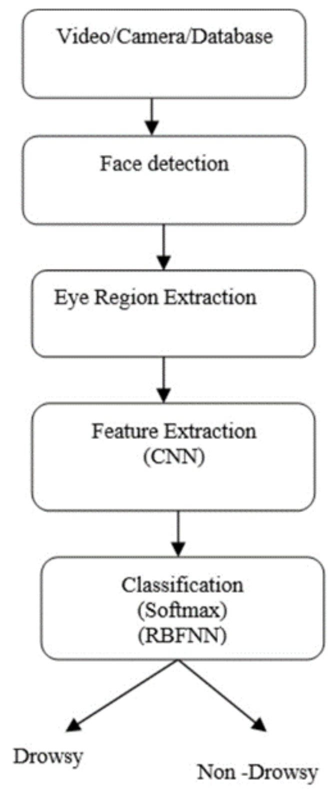

Figure 3. Deep CNN Based System [1][2]

3.2 Ensemble Approach Based on Four Deep CNN Models

The proposed architecture consists of two main parts, learning function representations and the ensemble module. Represent the learning characteristics using four models: AlexNet, VGG-FaceNet,FlowImageNet and ResNet. Each model has been trained on a standard (NTHU) drowsiness which contains videos of drivers, this is done to controlthe network depth to extract different features. Numerous convolutional layers, FC layers, parameters and number of neurons are used to extract features related to sleepiness, after which the model is trained. Post training this model and extracting features from the input images, each and every network is then tuned for fatigue classification which is multi class and is performed on the final SoftMax layerof every network. The ensemble strategy is used only in situations where the models give a non-negative result.[2][8]The first step is to process the input video which maybeone of four types, i.e, non-sleepy, sleepy, slow blinking

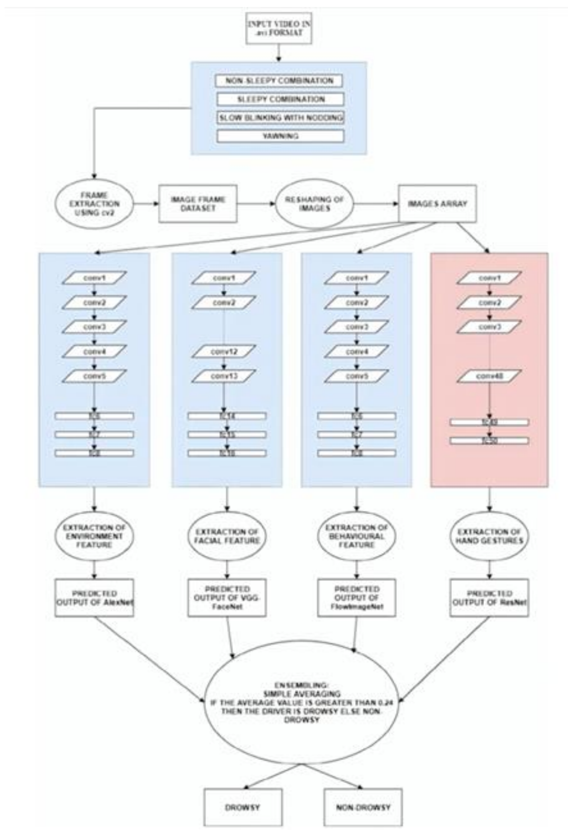

Figure 4. Ensemble Approach [2]

with nodding and yawning. The information gathered hereis passed into the frame extraction module which removes the noise present in the extracted video frame.

The extracted frame is sent to the image frame dataset, fromhere it is sent to another module responsible for reshaping these images so that all of the images captured are of uni- form dimensions. These images are then stored in an image array where each image is fed to all four CNN models, i.e., AlexNet, VGG-FaceNet,FlowImageNet, ResNet.

These CNN models generate predicted output after pro- cessing the input images. The predicted output of all these models are combined and fed to the ensemble model. In the ensemble model a simple average is done and based on the results generated, the image is classified as drowsy or non-drowsy.

IV. EEG AND ECG BASED DROWSINESS DETECTIONMETHODS

4.1 Long Short-Term Memory and EEG Based Method

The system proposed here is a camera system with two cameras wherein both the cameras are pointed towards the face of the driver. On each and every frame face detection followed by eye detection is done. In status quo, there are certain methodologies such as OpenCv MTCNN and dlib. When these methods were compared, the MTCNN based approach seemed to have the highest performance, hencethis method was implemented here. On both the cameraframes, a 48 by 48 pixel size area has to be cut near theeyes. Here, each input patch is mounted on 2304 area of same size.

Every single line represents the processing aspect of the input areas. These areas are part of the left-eye-left camera, right-eye camera, right-left-eye camera and left-right-left camera respectively, in every row the LSTM cells are opened in steps of n-time intervals.Finally, the two fully connected FC layers provides the final output step. This is a 2 gradehot coded output, which can either belon to ”sleep” or ”awake”.[5][12]

The changes of features in the EEG energy spectrum were fully analyzed and this was used to test and de- tect the presence of drowsiness in the drivers, the pre- dicted output belonged to either one of the two labels, ”awake”,”sleep+notify”. The four different EEG waveforms that were analysed were delta-band, theta-band, alpha-band, beta-band. After the application of the 60 Hz notch filter,the EEG signal was filtered through a 0.2 - 45 Hz band.

Post this, the Fourier short-term transition is applied to all the EEG channels, few power parameters are integrated with each and every EEG window in all channels. Under- standably, as the levels of EEG signals increase so doesthe power of awareness. This algorithm uses a variable reference that is said to be calculated on the EEG window that is moving and this is used to estimate the number of variables in the power values in each area at a time andto measure the level of monitoring frequency, the algorithm also reads a specific level limit of awareness level which are based on any changes in the power ratings present in the driving control session which are executed early in the morning when participants were extremely alert. If the level of awareness is below the limit, a state of ”drowsiness” is declared; if not, the status of the video frame is considered a ”warning”.[5][12]

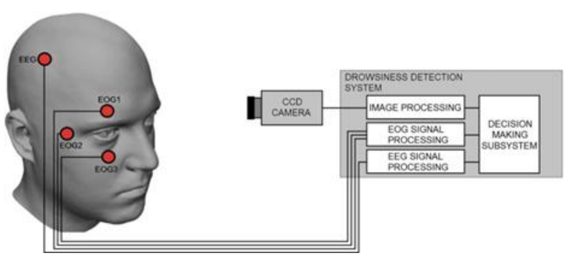

Figure 5. EEG Based Approach [5]

4.2 Drowsiness Detection Method Using Wearable ECG/PPG Sensors

This approach investigates the robust and identifiable pat- terns of (HRV) signals captured by the ECG and PPG

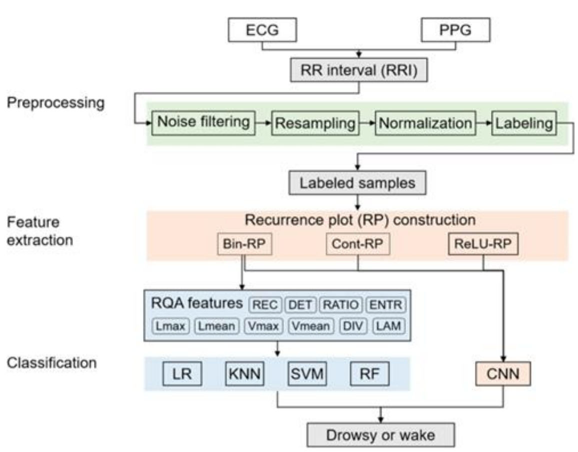

Figure 6. ECG/PPG Based Approach [12]

wearable sensors to detect driver drowsiness. It is said that wearable sensors are sensitive to slight movements, so the signal is often noisy. Therefore, it is necessary to find agood function from the noisy HRV signal that makes a good distinction between sleep and wakefulness.[12]

For this purpose, these recurrence plots (RP) - Bin-RP, Cont-RP, and ReLU-RP were examined, which were generated from the R-R interval (RRI) of the heartbeat. Here, Bin-RPis essentially a diagram which is binary recursive, Cont-RP is a diagram which is continuous recursive, and ReLU-RP is a diagram which is threshold recursive, these are obtained by completely filtering Cont-RP with some modified normal- ized linear unit function (ReLU). is. These RPs were used as an input function to a CNN to investigate their importance for sleepy / awakening categorization.[5][12]

In the drowsiness model, each and every type of RP is takenas an input to the convolutional neural network (CNN). Andunlike traditional methods that use limited hand-drawn fea- tures, CNNs can generate alternative features from specific RPs to distinguish between sleepy and awake areas.[12]

V. EXPERIMENTAL RESULTS

For the Deep CNN based methods the accuracy with which drowsy images were being predicted were extremelyhigh (¡95 percent). The proposed work was implemented us-ing Python 3.6 which was executed on the Jupyter Notebookand a Windows 10 based PC with a 2.4GHz CPU and 8GBRAM. The experiment carried out used 640x9x480 pixelsand 30 frames / sec audio-free in AVI format video.[2][8] In the Viola Jones approach over 1200 images were used while training to perform the experiment, 600 of which weresleepy and the other 600 were not. Over 500 images wereused for the purpose of validation, out of which around 250were sleepy and another 250 were not.Over 1150 imageswere used for testing, out of which 550 were sleepy images,

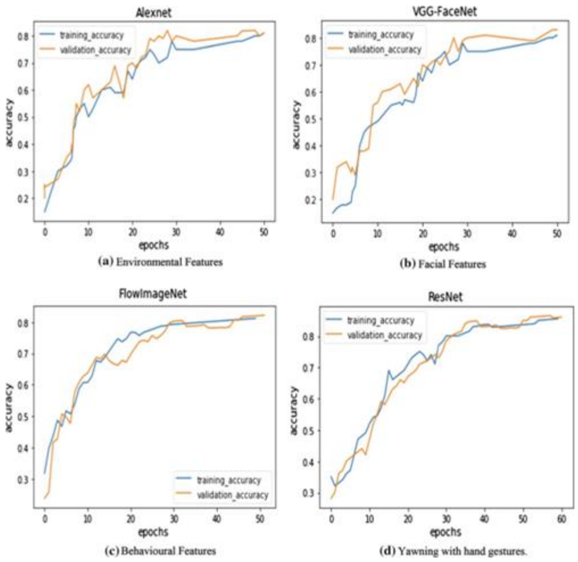

Figure 7. Ensemble Based Approach [2]

Type of features	AlexNet	VGG-FaceNet	FlowImageNet	ResNet	Ensemble
Facial	76.48	87.09	83.11	81.34	85%
Environmental	85.94	79.19	78.12	84.89	
Behavioral	82.09	75.11	86.14	77.12	
Yawning with hand gestures	78.11	79.66	83.11	87.05	

Figure 8. Ensemble Based Approach [2][8]

Training Samples	Testing Samples	Validation Samples	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
1200	1150	500	98	97	96.42

Figure 9. Viola-Jones Based Approach [1]

whereas 600 were not sleepy, and the proposed model achieved 96.42 percent accuracy.[1]

From the above results it can be incurred that even though the Viola Jones based approach has a greater accuracy, the Ensemble based approach takes into account a lot more detailed parameters, like the driver's environment and it's affect on the driver. Hence, even though the accuracy isn't very high as compared to the Viola Jones based approach, the Ensemble approach is much more thorough.

In the ECG/PPG based approach to evaluate the efficacy of all the RP type that detects drowsiness, over three different CNN models were constructed using the RPs as inputs.There are four classification models (LR, ANN, SVM, RF) with six important RQUA functions (p-value ¡0.05) and ReLU-RP seemed to have a better performance in distin- guishing between sleepy state and wakefulness. In particular,this RP offers the best performance in all aspects such as F number, accuracy, precision etc. The three RP models are 60 to 70 percent more accurate than existing models that have RQA capabilities. This model has around 53 -63 percent accuracy. [5][12]

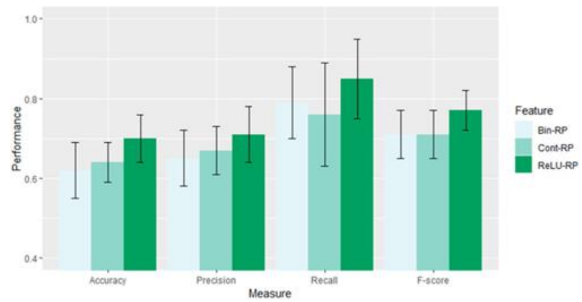

Figure 10. ECG/PPG Based Approach [5][12]

In the EEG based approach the authors combined the outputsfrom the final stages of the LSTM (which corresponds tothe inputs from both the eyes) to create final" awakening" and "sleepy" predictions. The test accuracy in C-LSTM is significantly higher than that in R-LSTM. At the end ofthe day, the results of the present approach show a higher level of agreement between the movements of both the eyes (detected by RNNs), furthermore, it shows that the EEG as an objective physiological measure of awakening, this showsthat wakefulness can be classified non-invasive with high accuracy, and when comparing the accuracy with a system that is based on machine learning and this uses the line-of- sight tracking function, the proposed method is significantlysuperior.

In this task, the data used was amalgamated in a lab set-ting. Research done in the future should consider takingthis technology to test in a setting very similar to real-world scenarios that also take into account more stringent conditions such as the use of coloured glasses, sun glassesor bad lighting.[5][12]

Epoch Size ⟶	5 s.	10 s.	15 s.	20 s.
Support Vector Machines (SVM)	83.6 %	82.7 %	84 %	83.8 %
Random Forest (RF)	84.1 %	84.5 %	85.1 %	85.9 %

Figure 11. EEG Based Approach [5]

These results cover both physiological features (like ECG, EEG signals) and behavioural features(like yawning) en-countered any driver. It can be observed that methods that largely depended on behavioural features had a greater accuracy than those that depended on physiological features.The main reason behind this disparity is the fact that meth- ods used to calculate physiological features are extremely intrusive and cumbersome and take in a lot of monetary and intellectual resources, hence in order to make it palatable to a regular driver a lot of technicalities need to be made simpler, as a consequence of this a lot of accuracy trade offsneed to be made.

VI. RESEARCH GAPS AND FUTURE SCOPE

All of the existing methodologies surveyed in this paper showcase high accuracy in terms of correctly classifying and predicting an image or a video as drowsy and promptly sending an alert or an alarm. However, there isn't an existingmethodology that not only correctly predicts and send an alert but also slows down the vehicle or sends an alert to an emergency contact.

If there was a methodology that slows the vehicle down or stops the vehicle when the driver crosses the threshold of permissible drowsiness, it would not only help save the life of the driver but it would also save the lives of the people around the vehicle and in turn reduce human deaths that are a consequence of such accidents.

Another aspect to delve into is much simpler than slowing down the vehicle. Instead of alerting the driver and thepassengers in the vehicle with the help of an alarm, if a methodology is developed to send an alert to any emergencycontact of the driver along with the vehicles coordinates,this would help the person who got the alert to contact any emergency services and save the lives of the people in the vehicle in case an accident occurs.

In status quo, all of the existing methodologies have anunderlying assumption that the driver's eyes aren't covered with any glasses. In most real world scenarios, many drivers wear sunglasses or eye sight glasses which hinder in the detection of drowsiness. In such scenarios, it is important to create a mechanism wherein the driver is asked to takeoff the sunglasses in regular intervals to notify the system that they are alert. If the eyes are covered with some form of covering, alternate mechanisms need to be created to prove the alertness of the driver at regular intervals.

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