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# NON-INTRUSIVE DROWSINESS DETECTION TECHNIQUES AND THEIR APPLICATION IN DETECTING EARLY DEMENTIA IN OLDER DRIVERS

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## Abstract

Drowsy drivers cause the most car accidents thus, adopting an efficient drowsiness detection system can alert the driver promptly and precisely which will reduce the numbers of accidents and also save a lot of money. This paper discusses many tactics and methods for drowsy driving warning. The non-intrusive nature of most of the strategies mentioned and contrasted means both vehicular and behavioural techniques are examined here. Thus, the latest strategies are studied and discussed for both groups, together with their benefits and drawbacks. The goal of this review was to identify a practical and low-cost approach for analysing elder drivers' behaviour.

### Keywords

Drowsiness; Fatigue; early-stage dementia; behavioural based; Vehicular based

## 1 Introduction

Drowsiness is one of the primary reasons for most road accidents that result in severe injuries and deaths. The risk increases with age as older age people suffer from fatigue during long journeys. According to National Highway Traffic Safety Administration (NHSTA), a total of 2.7 million people were injured or killed in 2019 that involved road accidents, out of which 1.9% of the accidents are due to drowsy driving. [1] These accidents mainly occur in mid-afternoon or between midnight and 6 a.m.

The current transportation system is insufficiently effective at resolving such challenges. As a result, researchers have devised a method for resolving this particular issue. By adopting a drowsy detection system that alerts a driver when they become sleepy, the rate of accidents can be drastically reduced

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The researchers have been working on a variety of strategies to combat this issue, and each methodology has its own set of pros and cons.

This paper is sectioned into 4 sections. In section 2 discusses the primary classification of techniques and their advantages and limitations. Section 3 discusses the detailed comparison between the techniques, their limitations and how to address those limitations. Section 4 is about how we designed a video-based system that can collect and detect driving behaviours of older drivers. And section 5 is the conclusion.

For selection of existing techniques, several domains and search engines were scouted during this review using different keywords for the selection of data. These domains include Google scholar, IEEE, Springer, ACM, Mendeley and ResearchGate.

A total of 567 papers were found with multiple keywords published in the above domains after 2015. The keywords were in multiple combinations to obtain those research papers. The initial search resulted 567 out of which we then selected a total of 15 papers by filtering through their title that is most relevant to our research and by thoroughly studying the abstract of those selected papers to give us a refined selection of relevant papers

## 2 Classification of Drowsiness Techniques

Drowsiness strategies are classified by how and why they are utilized. The advantages and disadvantages of each technique are compared. On the road, tired drivers are easy to spot.

### 2.1 Behavioural Based Detection Techniques.

Behavioural-based detection methods are non-intrusive. Eye blinking or proximity of eye for a given period of time, nodding of the head, and more frequent yawning are all measured. [2]. However, PERCLOS (Percentage of Closure) has been analysed and applied in numerous domains [3, 8–10], including commercial products like LEXUS. To identify drowsiness, researchers have also used eyebrow raises, lips, and jaw drops [5, 11] to identify current condition of the driver. However, evaluating behavioural elements has certain drawbacks and relies heavily on external influences. One of them is light. Night photography is difficult due to lack of light [5]. Although infrared cameras function better than normal cameras [12], they are not considered sturdy. Most behavioural measures are assessed using data gained by simulating tired drivers rather than real-time drowsy drivers. Their eyes and mouth are detected using various techniques. A few examples are HAAR algorithm, Cascade Classifier, Hough Transform, and Gabor filter.

**Eyes Tracking -—**In order to detect drowsy drivers, vision-based devices are employed to record and track eye movement and closure [14]. The data was acquired in 1–2 hours for ten selected drivers yielded useful insights. Participants' data were collected and analysed using fuzzy K-nearest neighbour with jack-knife validation. Table 1 shows an average accuracy of 88.75 percent.

While some of the publications studied and analysed had superior findings, none used FKNN to obtain them. This data collection used a specific type of camera placed in glasses or other form of hanging near the eye to capture the pupil from a very close distance as seen in image below.

**Eye's Aspect Ratio -—**Fatima et al [29] presented an approach based entirely on the driver's sight. They employed the Voila-Jones method to recognize the face and eyes, and two classifiers to determine whether the eyes are closed or open. They employed SVM and AdaBoost to classify the pupils. They tested it in various automobiles and lighting conditions to collect a dataset for SVM and AdaBoost. Their research found that SVM performed better than AdaBoost, with 93% accuracy versus 87% for AdaBoost. Eye-Aspect Ratio is used in conjunction with Eye tracking to improve accuracy. Anwar [34] combined EAR with eye tracking and found improved eye detection and tracking accuracy. They computed the EAR by eye blinking. Blinking occurs when the horizontal line gets shorter than a particular threshold. The EAR may be determined using the markers in fig 2.

81 facial features shape predictor [35] was used to identify the feature in the figure above. After identifying facial traits, they take eye datapoints and use the algorithm below to determine the EAR.

$$EAR = \frac{\| |p2 - p6| + |p3 - p5| \|}{2||p1 - p4||} \tag{1}$$

By using the EAR, though it's a good way to analyse the drowsiness of the driver, it still has drawbacks. As the eyes shape for every person is different the threshold that is used is different for every person. So, concluding a single threshold for every person is not an efficient approach. Anwar [34] tested that on different people with different eye shapes as shown in table

**Mouth and Yawning based on CNN -—**Analysing driver fatigue based on yawning is also an effective method. Xie Y. et al. [15] presented convolutional neural network to train the model for detecting yawning, and the results turn out to be very efficient. The architecture of the model comprises of inception-v3 that is used for feature extraction as shown in figure below because among the many other models like VGG[16], ResNet[17], it has the highest accuracy and low volume of weights. An extension layer, Long Short-term memory (LSTM), was added to it and then trained. This model is trained on a public dataset called Yawning Detection dataset (YawDD)[18]. It was able to achieve an accuracy of 97.36% [2].

Another similar study is also conducted based on CNN using the same datasets by Savas et al. [20], but instead of using transfer learning, they trained the multi-task CNN and then using a classifier to classify the fatigue level. The architecture is somehow more complicated and complex then previous one but have better results. It was able to achieve accuracy of 98.81% which is few point better than the last one which had accuracy of 97.36%.

But training a model is based on how clean the data is. Noise in data can have a negative impact when it comes to machine learning. Salekshahrezaee et al [33] shows that a noisy data usually requires more instances to train a predictive model that can be effective.

**Facial Expression Representation -—**To prevent accidents of drowsy drivers, Liu Z. [19] came up with a solution to detect the state of the driver by comparing two facial expressions that are based on eyes and mouth combined. The researchers came up with a solution to combine the frequency of yawning and the percentage of eyes closure called PerClos [28]. Perclos one of the most effective techniques to measure drowsiness. The reason for its effectiveness is that instead of counting each event, it takes an average for a certain interval. It’s derived as

$$PerClos = \frac{No.\ of\ Frames\ with\ eyes\ closed}{Total\ frame(3\ minutes) - \ Blinking\ rate} \tag{2}$$

As for the detecting status of eyes, whether they are closed or open is based on the aspect ratio of the eyes. Eyes corners and landmarks such as the upper eyelid and lower eyelid are detected using Harris Corner, and the open or close ratio is calculated by computing the distance between eyes landmarks to get a mid-point. The derived formula is as follows.

$$mid - point \quad = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}\right) \tag{3}$$

This gives us coordinates of the midpoint, and from the midpoint, we calculate the distance of eyelids to know if they are open or close. The distance is calculated using the distance formula as follows

$$distance \quad = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{4}$$

Combining PerClos with the frequency of yawning gave them very satisfying and accurate results. They used Multi-Block Local Binary Pattern and AdaBoost classifier to detect facial key points based on their calculation of PerClos and to yawn on that. After processing, they used an inference system to classify the states into three categories, i.e., normal, slight, and severe drowsy. Another technique that is also useful when it comes to facial expressions are emotions. Altaher et al [32] came up with a CNN model that can recognize face emotions. Although the context of using a CNN with it such environment is more like to have a lot of false positives.

**Eyes State and Head Pose with Depth -—**To prevent and lower the percentage of accidents because of drowsiness, L. Zhang et al. [36] came up with a solution that utilizes depth cameras instead of using regular cameras. RGB-D images are rich in information have instead of having just RGB values. Furthermore, it has an extra parameter that denotes the depth of the image. Due to depth, one can know the distance between the centre from the camera to the object, and it can measure the depth of each item by representing it in the form of a heat map. Their approach is based on the eye’s state and the pose of the head. Eye’s state is treated as binary classification by using Weber’s Local Binary Pattern (LBP), and head pose is estimated by simply the difference in the angle between the new position of the head position and the previous position.

Fig 3 shows flowchart of the framework that is used in this paper to detect the drowsiness of a driver by utilizing Microsoft Kinect Camera which has the capability of capturing driver in 3 dimensions, the depth as 3rd dimension, and then using that to come up with results. Their system was able to recognize the eye's state with an accuracy of 96.63% with no noise levels and 81.71% with the highest level of noise as reported in their paper.

**Eyes Blink Velocity Detection -—**Blinking is a typical trait used to detect driver drowsiness. A reliable method for classifying blinking can lead to a powerful drowsiness detection system. Baccour et al. [21] suggested a method for detecting eye blinking based on blinking velocity. When tired, the pattern of blinking alters dramatically. The algorithms use k-mean clustering to classify the eyelid velocity into nine categories, 1 being extremely alert and 0 being excessively tired. The Savitzky-Golay filter [22] is used to smooth the signal.

**Blinking Rate -—**Eyes are the best facial characteristic for recognizing tired drivers. Rahman et al. [26] recommended measuring the open/close aspect ratio to monitor eye condition. They used the viola-jones face detector method [27] to detect the face and then Haar cascade to detect the eyes. The distance between the upper and lower eyelids is estimated using the midpoint formula, which is found using the Harris corner detector. The disadvantage of such an algorithm is that it is influenced by lightning and so cannot be used at night.

### 2.2 Vehicular Based Detection

General, vehicular detection techniques are classed as semi-intrusive procedures since they can be classified into two groups. The non-intrusive techniques will be considered for now. Vehicle speed variability and steering wheel angle are among the non-intrusive strategies used in vehicular detection. They all have limitations and are easily affected by external elements such as weather, darkness, roads and traffic. The results of some countermeasures are unsatisfactory. Because traffic can cause frequent lane changes and shorten commute times, the researchers tried to mitigate the effect by setting a threshold.

**Lane Detection -—**There are numerous lane detecting techniques, each with its own set of benefits and drawbacks [23] i.e Hough Transform, Fuzzy Logic etc. If the lane is a straight line, Hough transform approaches works well. Since road models are largely mathematical calculations, they may perform effectively when data is unavailable or noisy. Fuzzy logic is utilized when there is a vast amount of faulty data and drawing conclusions is impossible.

**Steering Wheel Velocity -—**Most of the techniques described are insufficient to prevent accidents so Gao Z. et al. [24] came up with a new approach to monitor drowsiness that does not require any hardware but can be integrated into existing equipment. The researchers studied the steering wheel's angle over time. It is proposed that it be examined and matched with measured criteria obtained during the exhaustion condition. They were able to test the results and exhibit good performance, proving that the procedure works.

Above figure show a series of the steering wheel angular velocity from which they determine a fluctuation in the series. That fluctuation is then used to distinguish the threshold set for concluding drowsiness driver.

Based on the fluctuations determined in the data to set a threshold for drowsiness, figure above shows that test results. The data is manipulated and only set to determine the drowsiness by only visualizing the abnormal areas in series. As shown in above figure $10^{th}$ and $50^{th}$ second status is detected as drowsy, which after carefully analysing the angle value, clearly shows that detected areas shows sign of drowsiness.

**Yaw Angle and Steering Wheel Angle using Time-series —**Zuojin et al. [25] also suggested evaluating the yaw angle and the steering wheel angle. It uses yaw and steering wheel angle time series data to calculate approximate entropy. ApEN is calculated as follows

$$ApEN(m, r, N) = \frac{1}{N - m + 1} \times \sum_{i=1}^{N-m+1} \log(C_i^m(r)) - \frac{1}{N - m} \sum_{i=1}^{N-m} \log\left(C_i^{m+1}(r)\right) \quad (5)$$
$$where\ C_i^m(r) = \frac{B_i}{N - m + 1}$$

Using backpropagation, a multi-layer sensory neural network classified it into three levels: normal, drowsy, and very drowsy (figure 3).

They used ten drivers with an average age of 28 and 4.3 years of experience to test the suggested method. The route chosen was the 2.5 hour freeway route from Beijing to Qinhuangdao. Table shows the gathered samples from the experiment.

Figure shows time series distribution of steering wheel angle and yawning They can produce better results when combined than when used separately. The combination of these measures can help detect drowsiness in senior drivers, in particular.

**Lane Heading Difference.—**Morris et al [30] suggested an approach that is more effective and accurate than other strategies used to detect drowsy drivers. They employed vehicle lane difference and lane position variability to assess driver fatigue. This strategy outperforms previous statistical methods at night and in low sleepy drivers. It checks for drowsiness by measuring reaction time, attentiveness, and oculomotor movement.

## 3 Comparative Analysis

Every technique discussed in this paper has its own pros and cons, and depends upon difference types of factors i.e some maybe effected by light that may not perform well at night while some may be effected by the visibility of the road signs.

Both categories are not sufficient to get an accurate result about the condition of the driver although, with time, many improvements and advancements have been made, we are not there yet to get accurate results from visual data due to the limitation of processing resources and also a limitation of visual devices that are used to get the data. The behavioural based techniques are considered much accurate as compared to the vehicular when it comes to non -intrusive detection techniques due to the fact that they give us information about the condition of the driver by analysing the facial expression and position of the driver to make a sufficient conclusion about the driver being drowsy of not.

Figure shows a simple comparison between the accuracies of the techniques used but that since we are dealing with video and images data a single metric of comparison cannot conclude that it will the best. Even though the techniques used have greater accuracy, there is still some limitations to them. Below are some of the limitations for these techniques discussed and a few suggestion on how it can be improved

Table shows the limitations that existing techniques have and a few suggestions that can be applied to improve those techniques. These techniques have greater capability when combined with other techniques to achieve more accurate results and will have a more robust application in terms of results. The improvements are just a suggestion made by studying different techniques for this study and can be improved by using many other techniques.

## 4 Designing of Video-Based System for Dementia detection in older drivers

In order to help professionals decide and recognize early-stage dementia and Alzheimer, we reviewed approaches and algorithms for detecting driving habits of drivers.

### 4.1 Activities in Phase of the Project

In this phase of the project our activities consisted of:

1. Designing the sensor and video system to be installed in the cars.
2. Selecting the components of the system (i) Telemetry system, and (ii) Video system.
3. Testing the components of the system.
4. Measuring drivers' indices using built-in AI algorithms.
5. Selecting techniques for video analysis and started implementing related algorithms.

### 4.2 Architecture of the Video System

The system installed in the car will consist of (i) Telemetry system, and (ii) Video system. Here we describe the video system and present results obtained for the first group of drivers.

Figure 1 shows a video system with two cameras and a large storage MDVR. The DSM camera analyses the driver's behaviour, while the front camera analyses the road surroundings.

**Driver behavior Indices -—**Our method involves recording and analysing video of the driver's conduct. Every 3 months, we release this video to track driver behaviour. Aside from visual analysis, telemetry provides a set of indices.

In this section we describe driver behaviour indices that we measured based on video from the DSM and forward cameras and AI algorithms applied in MDVR, as shown in Tables 7 and 8.

### 4.3 Data Collection

This is based on an analysis of the first 10 drivers who drove between 1 and 3 months. The annual storage requirement is 400 GB. One driver would need 1.2 TB of storage over three years. However, we assumed in our analysis that the requirement for one driver working in the project would be 1 TB.

Based on the preliminary analysis Table 10 presents storage analysis for 1, 100, 200, and 750 drivers.

The numbers mentioned above were an estimation of the storage that was based a certain number of drivers and their average. These numbers are changed for every driver and the time spent driving. Table below shows the details storage for 10 drivers and the storage based on the hours of driving.

### 4.4 Results

We recorded and evaluated results for 10 senior drivers, who drove cars for several months. Here we present results from DSM and front cameras for two drivers and analyse these results. The AI algorithms analysed videos from the drivers and provided indices stored in the log file. We created a program to analyse the log file and extract various indices. As an example, results for Driver with ID 1001 are shown for May 2021 in Tables 3 and 4.

At this time of the project, the following indices show relatively large numbers, which can be used to define driver's behaviour:

1. From DSM camera:

    - Closing eyes (at least for 3 seconds or more) and
    - Turning the head (or distraction).

    The other indices, such as

    - Yawning,
    - Using the smartphone, and
    - Smoking is usually either zero or very small except from false positives

2. From front camera:

    - Crossing lines, and
    - Being close to another car (Near Collision)

    Other indices are zero or close to zero:

    - Passing red light,
    - Being close to pedestrians, and
    - Near collision detection

As to understand the full workflow of the data extraction process, below figure can shed some light on the whole process of the workflow from cameras to the dynamic table that was filled. As show in the figure we used the log files instead of using the actual pictures that was because the AI algorithms bult-in into the system already have processes that in real-time and using the log files was a more optimized and less time and resource consuming. For the future work these indices along with its screenshots that was AI classified as well as our own classification of some other indices, will be used with these to get better results. Cleaning and validating the data techniques will be performed to make that results more accurate.

## 5 Conclusions

Our primary objective in producing this research was to examine all of the strategies that are non-intrusive to the drivers' ability to drive. We examined all of the most recent methodologies and strategies that have been given for the identification of drowsy drivers and compared them to one another in order to gain a clear understanding of which techniques function in which conditions and environments. Taking a look at the strategies discussed above and their results, we can conclude that if a person is concerned with non-intrusiveness when it comes to identifying drowsy drivers, behavioural tactics are far more effective than vehicular techniques. We created an architecture by combining several devices that were purchased specifically for the purpose. With the use of those devices, we were able to analyse the driving behaviour of the participants and present it in a tabular format that could be displayed and thoroughly investigated for the diagnosis of dementia and early-stage Alzheimer's disease.

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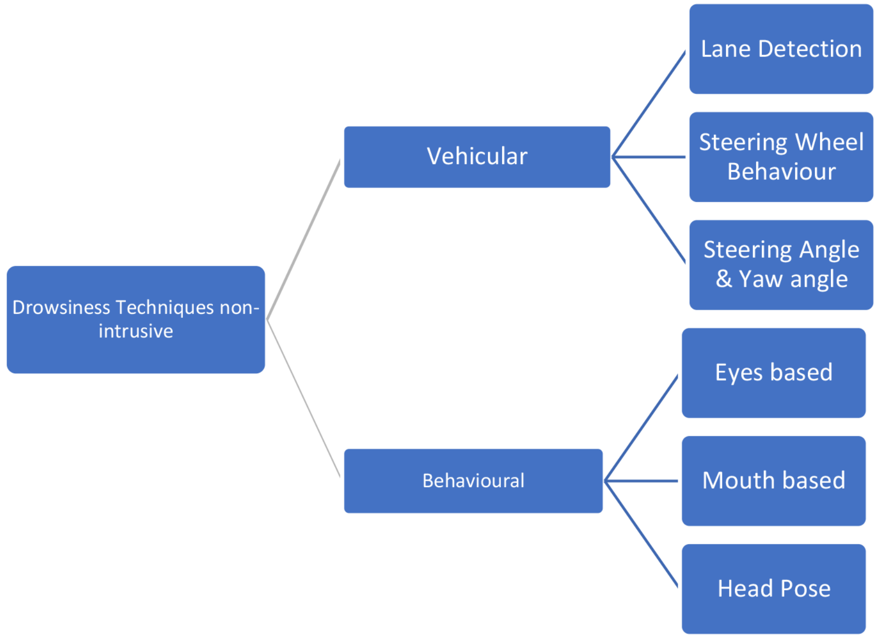


**Figure 1.**
Classification of Non-Intrusive Drowsiness Techniques


**Figure 2.**
DLab Equipment for capturing pupils

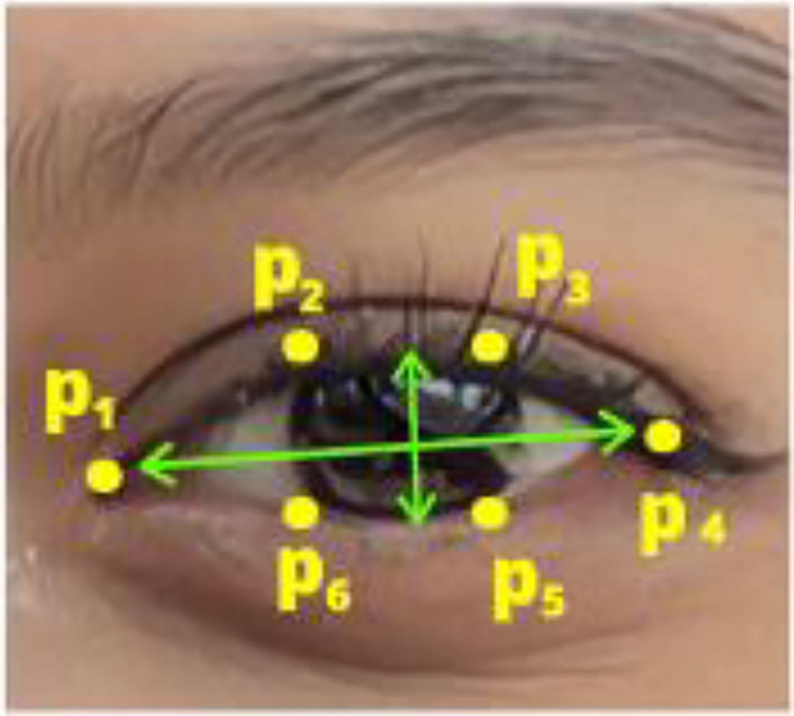


**Figure 3.**
Eye's Landmarks [34]

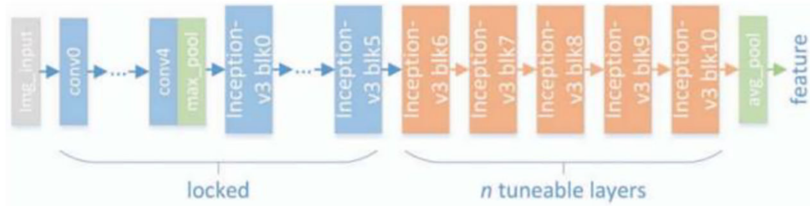


**Figure 4.**
Inception Layer with tuneable and locked layers

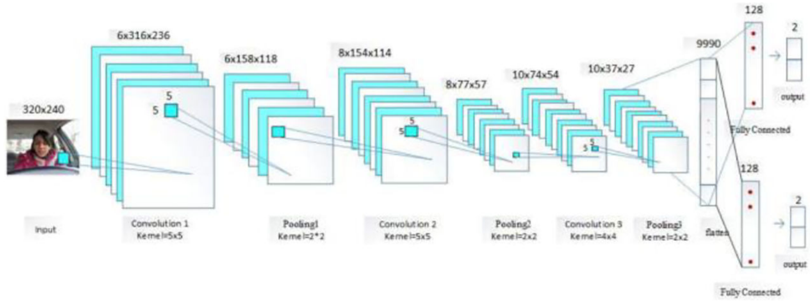


**Figure 5.**
Multi CNN Model

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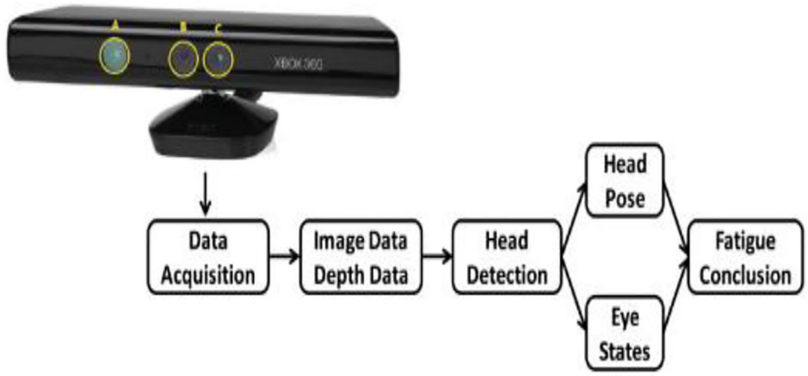


**Figure 6.**
Framework used by utilizing Microsoft Kinect with Depth Camera [36]

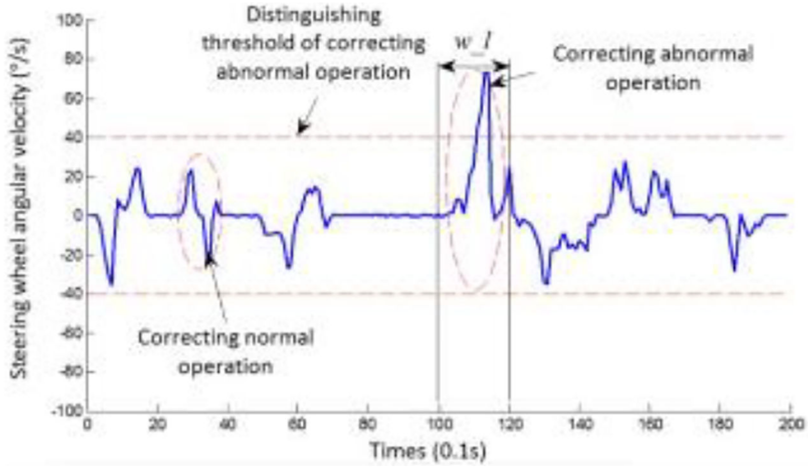


**Figure 7.**
Series of SWA Velocity in Drowsy Drivers

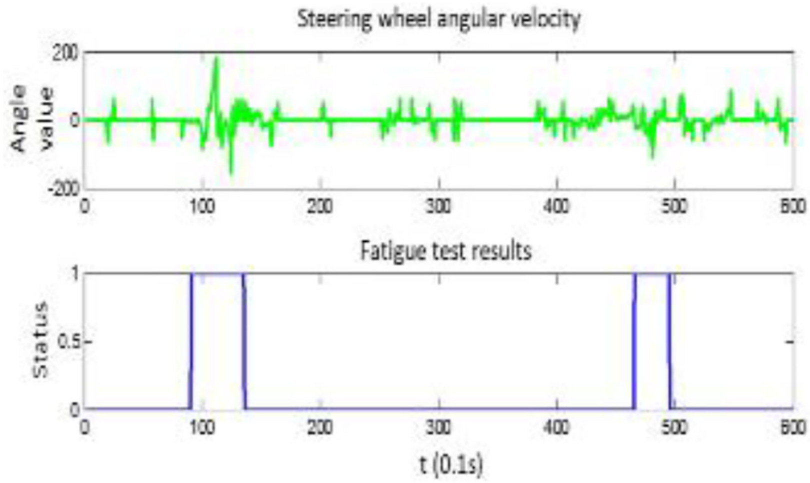


**Figure 8.**
Test results of manipulated data

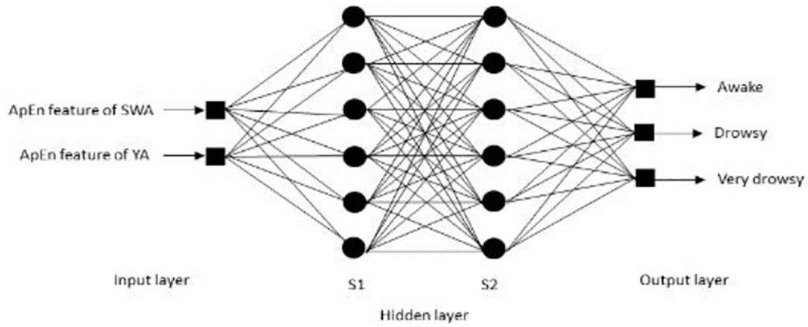


**Figure 9.**
Network Architecture for Back Propagation [25]

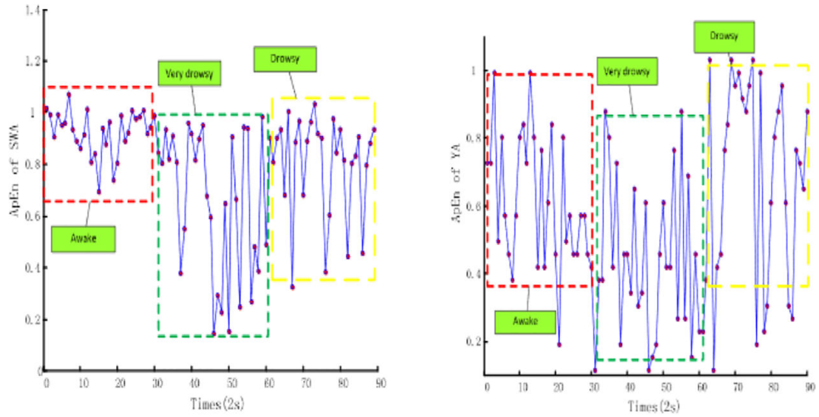


**Figure 10.**
ApEn Distribution of Steering wheel Ange and Yawning [25]

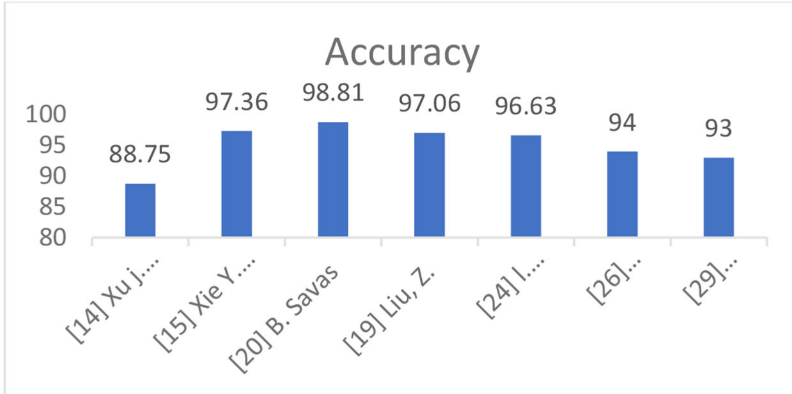


**Figure 11.**
Accuracies of selected papers


**Figure 12.**
The architecture of the video system.

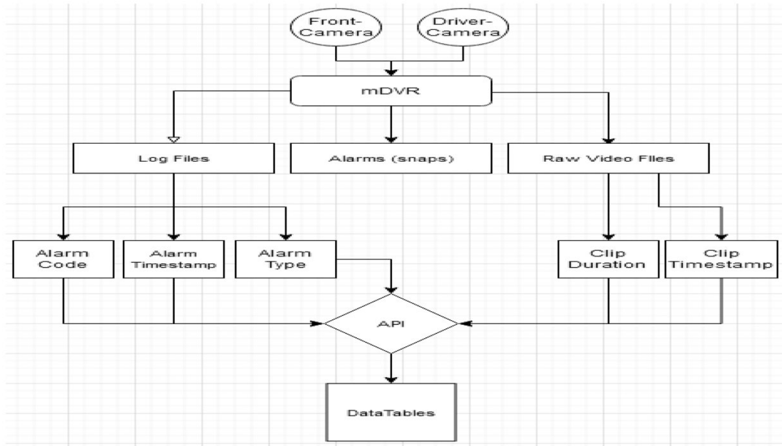


**Figure 13.**
Workflow of Data extracted in above table.

**Table 1.**

Jackknife Cross-Validation test results [14]

| Subject No | Accuracy % |
|---|---|
| 1 | 88.56 |
| 2 | 88.91 |
| 3 | 88.49 |
| 4 | 89.01 |
| 5 | 88.52 |
| 6 | 88.32 |
| 7 | 87.82 |
| 8 | 88.86 |
| 9 | 88.7 |
| 10 | 88.59 |
| Mean + Variance | 88.75 + 0.116 |

**Table 2.**

Eye Blinking Ratios

| Human Subject | Eye Blinking Ratio |
|---|---|
| Person 1 | 3.48 |
| Person 2 | 3.59 |
| Person 3 | 3.72 |
| Person 4 | 5.11 |
| Person 5 | 3.48 |
| Person 6 | 3.84 |
| Person 7 | 5.24 |
| Person 8 | 4.02 |
| Person 9 | 3.51 |
| Person 10 | 3.48 |
| Person 11 | 3.49 |

**Table 3.**

Behavioural Based Techniques

| Reference | Features | Techniques | Accuracy |
|---|---|---|---|
| Xu j. et al. [14] | Eyes Tracking | Fuzzy K-Nearest Neighbour | 88.75 |
| Xie Y. et al [15], VGG[16], ResNet [17] | Mouth & Yawning | CNN, LSTM | 97.36% |
| B. Savas[20] | Mouth & yawning | CNN, SVM | 98.81% |
| Liu, Z. [19] | Eye Closure and Freq. Yawn | MB-LBP, AdaBoost, Fuzzy Inference | 97.06% |
| l. Zhang et al. [36] | Eye state & Head Pose | WLBP, SVM | 96.63% |
| Baccour [21], Savitzky-Golay [22] | Eye Blink velocity | Signals, Savitzky-Golay | nil |
| Rahman et al. [26] | Blinking rate | Voila-Jones, Haar Cascade Classifier, | 94% |
| Fatima et al. [29] | Open/Close Eyes | Voila-Jones, SVM, AdaBoost | 93% |

**Table 4.**

Sample Database of data collected [25}

| Serial No. of Subjects | Number of Samples | Fatigue Level |
|---|---|---|
| 910_002 | 34 | (0,1) |
| 910_004 | 48 | (0,1,2) |
| 911_003 | 29 | (0,1) |
| 912_007 | 24 | (0,1) |
| 913_002 | 23 | (0,1) |
| 913_004 | 54 | (0,1,2) |

**Table 5.**

Vehicular-based Techniques

| Reference | Features | Techniques | Accuracy |
|---|---|---|---|
| Date et al. [23] | Lane Detection | Hough Transform, Fuzzy logic, Road Model | nil |
| Gao Z. [24] | Steering Behaviour | Temporal detection window | nil |
| Zuojin et al [25] | Steering wheel angle and yaw angle | MLPNN, back propagation, Approximate entropy | 88.02% |
| Morris et al. [30] | Lane difference and variability | Hough Transform | nil |

**Table 6.**

Categorical Comparison of Drowsiness Techniques

| Category | Techniques | Pros | Cons |
|---|---|---|---|
| Behavioural Based | Eye blinking, PerClos, yawning, Head-pose etc. | Simple implementation | Effected by light, low reliability |
| Vehicular Based | Lane detection, Steering wheel etc. | Easy to use | Effected by external factors, limited information, |

**Table 7.**

Comparison and improvements in existing techniques

| | Technique/Type | Limitations | Improvements |
|---|---|---|---|
| **Behavioral** | Eyes tracking | Visibility, glasses, light impact | Infrared-cameras |
| | Mouth and Yawning | head position, light | Angle of camera, infrared cameras |
| | Eye Closure and frequency | Glasses, light | Multi-sensor approach, infrared cameras |
| | Head Pose and Eye state | Angle, Visibility, height varies | Infrared-cameras, adjustable height cameras, multi sensor approach |
| | Eye blinking velocity | Light, glasses | Multi-sensor approach |
| | Blinking rate | Light, glasses | Multi-sensor approach, infrared cameras |
| **Vehicular** | Lane detection | Visibility | Prediction, object detection |
| | Steering wheel behavior | Alignment, driving pattern | Multi-sensor approach |
| | steering wheel angle | Alignment | internal sensor, multi-sensor, predictions |
| | lane difference and variability | sensor depended | behavioral techniques |

**Table 8.**

Driver Facing Camera Indices

| Behavior Indices | Description |
|---|---|
| Face detection | The AI algorithm detects the face of the driver and the driver's features. |
| Eyes detection | The AI algorithm detects the eyes and analysed weather driver eyes are open or closed. |
| Yawning | Yawning is based on eyes and mouth detection. |
| Distraction | Distraction is based on the head-pose angle. Head-pose estimation technique was applied but the initial angle is adjusted due to the placement of the camera on dashboard |
| Smoking & Mobile Phone | Both of these indices use AI object detection algorithms to detection. |

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**Table 9.**

Front Facing Camera Indices

| Behaviour Indices | Description |
|---|---|
| Traffic sign detection | The AI algorithm detects the traffic signals and monitor if the driver passes on red sign or not |
| Object detection | The AI algorithm detects objects on the roads, such as pedestrian or cyclist crossing the road, curbs or barriers, nearby vehicles, and others. |
| Lane Crossing | AI algorithm that can detect lane departure |
| Near-Collision | AI algorithm that can detect object or vehicle at a certain distance from it. |
| Pedestrian Detection | AI algorithm that can detect whether the driver yield at for the passenger crossing. |

**Table 10.**

Storage Details

| # of Drivers | 3 Months | 1 Year | 3 Years |
|---|---|---|---|
| 1 | 100GB | 400GB | ~1TB |
| 100 | 10TB | 40TB | ~100TB |
| 200 | 20TB | 80TB | ~200TB |
| 750 | 75TB | 300TB | ~750TB |

**Table 11.**

10 Drivers storage

| Driver-ID | Days | Hours | Storage |
|---|---|---|---|
| 1001 | 47 | 77 | 126.59 |
| 1027 | 16 | 19 | 66.73 |
| 1029 | 75 | 297 | 153.47 |
| 1025 | 73 | 160 | 481.7 |
| 1018 | 151 | 287 | 419.76 |
| 1009 | 50 | 57 | 61.32 |
| 1010 | 23 | 40 | 53.21 |
| 1015 | 7 | 7 | 5.74 |
| 1023 | 24 | 23 | 17.89 |
| 1006 | 74 | 84 | 125 |

**Table 12.**

Driver 1001, Driver's Camera (Yawning, Smoking and Mobile Phone not Included)

| Driver ID | Date | Duration (min) | Closing eyes (total) | Closing eyes (per 10 min) | Distraction (total) | Distraction (per 10 min) |
|---|---|---|---|---|---|---|
| 1001 | 5/3/2021 | 76 | 8 | 1.1 | 8 | 3.8 |
| 1001 | 5/4/2021 | 61 | 10 | 1.6 | 10 | 8.9 |
| 1001 | 5/10/2021 | 114 | 1 | 0.1 | 1 | 8.5 |
| 1001 | 5/11/2021 | 23 | 0 | 0 | 0 | 5.5 |
| 1001 | 5/12/2021 | 110 | 6 | 0.5 | 6 | 2.7 |
| 1001 | 5/13/2021 | 32 | 15 | 4.6 | 15 | 8.2 |
| 1001 | 5/17/2021 | 34 | 6 | 1.8 | 6 | 17.9 |
| 1001 | 5/19/2021 | 183 | 6 | 0.3 | 6 | 3.7 |
| 1001 | 5/22/2021 | 32 | 0 | 0 | 0 | 9.9 |
| 1001 | 5/24/2021 | 121 | 1 | 0.1 | 1 | 2.7 |
| TOTAL & AVERAGE | | Total: 667 | 53 | | 455 | |
| | | Aver/day: 67 min | 5.3 per day | 0.8/10min | 4.5 per day | 6.8/10min |

**Table 13.**

Driver 1001, Front Camera (passing stop sign, red light and near pedestrian are not included)

| Driver ID | Date | Duration (min) | Crossing lanes (total) | Crossing lanes (per 10 min) | Near collision (total) | Near collision (per 30 min) |
|---|---|---|---|---|---|---|
| 1001 | 5/3/2021 | 76 | 4 | 0.5 | 0 | 0 |
| 1001 | 5/4/2021 | 61 | 8 | 1.3 | 0 | 0 |
| 1001 | 5/10/2021 | 114 | 0 | 0 | 0 | 0 |
| 1001 | 5/11/2021 | 23 | 1 | 0.4 | 0 | 0 |
| 1001 | 5/12/2021 | 110 | 2 | 0.2 | 0 | 0 |
| 1001 | 5/13/2021 | 32 | 1 | 0.3 | 0 | 0 |
| 1001 | 5/17/2021 | 34 | 15 | 4.4 | 0 | 0 |
| 1001 | 5/19/2021 | 183 | 2 | 0.1 | 0 | 0 |
| 1001 | 5/22/2021 | 32 | 0 | 0 | 0 | 0 |
| 1001 | 5/24/2021 | 121 | 0 | 0 | 0 | 0 |
| AVERAGE | | Total: 667 | Total: 33 | | | |
| | | Aver/day: 67 min | Aver/day: 3.3 | 0.7/10min | 0 | 0/30min |