**CHAPTER 2**

**LITERATURE REVIEW**

Nowadays, many people lose their lives due to fatal road accidents around the world and drowsy driving is one of the primary causes of road accidents and death. The term “drowsy” is substitutable with sleepy, that merely means that an inclination to fall asleep. The stage of sleep is often classified as awake, non-rapid eye movement sleep(NREM), and rapid eye movement sleep(REM).

**2.1. Features of Drowsiness**

One of the challenges in developing an economical drowsiness detection system is a way to acquire proper drowsiness information. Because of safety reasons, drowsiness cannot be manipulated during a real environment, Therefore the drowsiness detection system needs to be developed and tested in a laboratory setting. However, in a laboratory setting, the foremost reliable and informative information that pertains to driver drowsiness depends only on the approach in which the driver falls into the drowsy state. Driver drowsiness principally depends on the quality of the last sleep, the biological time (time of day) and the rise within the period of the driving task. In some analysis experiments, the subjects were totally deprived of sleep, whereas they were only part deprived of sleep in others. Additionally, some researchers recruited night shift staff as their subjects, in this case, the subjects were entirely deprived of sleep as results of the experiments were conducted within the morning. Kokonozi, et al. Conducted an experiment during which they monitored the participants for twenty four before the experiment began to make sure that they were utterly sleep deprived. In certain experiments, researches partly deprived the subjects of sleep by permitting them to sleep for less than a half dozen. Peters, et al. Studies an equivalent subject throughout four consecutive days and regarded the results of no sleep deprivation, partial sleep deprivation and total sleep deprivation on their drowsiness level. They discovered that, even within the case of partial sleep deprivation, the subjects tend to urge drowsy after a while. Hence, the standard of the last sleep is a crucial criterion that influences drowsiness. Otamani, et al. Found that sleep deprivation alone doesn’t directly influence the brain signals that control, drowsiness, whereas the period of the task includes a strong influence. Researchers have additionally inferred that prolonged driving on a boring setting stimulates drowsiness. In fact, it has been discovered that the subjects will become drowsy at intervals twenty to twenty-five min of diving.

**2.2. Drowsiness Detection**

In order to detect drowsiness of drivers, numerous approaches have been proposed. This section summarizes the existing approaches to detect drowsiness.

Rateb et al. (R. Jabbar, K. Al-Khalifa, M. Kharbeche, W. Alhajyaseen, M. Jafari, and S. Jiang,2018) detected real-time driver drowsiness using deep neural networks. They developed an Android application. Tereza Soukupova et al. (T. Soukupova and J. Cech,2016) used EAR(Eye Aspect Ratio) as a standard measure to compute drowsiness of a person. They also detailed the types of systems used for detecting drowsiness of driver. For example, Active Systems (considered as reliable, but use special hardware that are expensive and intrusive like infrared cameras etc.) and Passive Systems (are inexpensive and rely on Standard cameras).

Manu B.N in 2016, has proposed a method that detect the face using Haar feature-based cascade classifiers. Initially, the algorithm needs a lot of positive images (images of faces) and negative images (images without faces) to train the classifier that will detect the object. So along with the Haar feature-based classifiers, cascaded Adaboost classifier is exploited to recognize the face region then the compensated image is segmented into numbers of rectangle areas, at any position and scale within the original image. Due to the difference of facial feature, Haarlike feature is efficient for real-time face detection. These can be calculated according to the difference of sum of pixel values within rectangle area and during the process the Adaboost algorithm will allow all the face samples and it will discard the non-face samples of images.

Amna Rahman in 2015, has proposed a method to detect the drowsiness by using Eye state detection with Eye blinking strategy. In this method first, the image is converted to gray scale and the corners are detected using Harris corner detection algorithm which will detect the corner at both side and at down curve of eye lid. After tracing the points then it will make a straight line between the upper two points and locates the mid-point by calculation of the line, and it connects the mid-point with the lower point. Now for each image it will perform the same procedure and it calculates the distance ‘d’ from the mid-point to the lower point to determine the eye state. Finally, the decision for the eye state is made based on distance ’d’ calculated. If the distance is zero or is close to zero, the eye state is classified as “closed” otherwise the eye state is identified as “open”. They have also invoked intervals or time to know that the person is feeling drowsy or not. This is done by the average blink duration of a person is 100-400 milliseconds (i.e. 0.1-0.4 of a second).

(S. Sangle, B. Rathore, R. Rathod, A. Yadav, and A. Yadav,2018) used a camera fixed on the dashboard to capture and send images to Raspberry Pi server installed in the vehicle, to detect faces using Harr classifier and facial points using the Dlib Library. Vibin Varghese (V. Varghese, A. Shenoy, S. Ks, and K. P. Remya,2018) detected landmarks for every frame captured to compute the EAR (between height and width of eye) using the landmark points of face. After computing the EAR; (V. Varghese, A. Shenoy, S. Ks, and K. P. Remya,2018) determined the driver as drowsy if the EAR was less than the limit for 2 or 3 seconds (because the eye blink lasts approximately 100-400ms).

Ashish Kumar( A. Kumar and R. Patra,2018) used Mouth Opening Ratio as a parameter to detect yawning during drowsiness. There are several other research works that have been conducted to determine vision based drowsiness detection (I. García, S. Bronte, L. M. Bergasa, J. Almazán, and J. Yebes,2012)– (K. Srijayathi and M. Vedachary,2013), fatigue detection (A. Chellappa, M. S. Reddy, R. Ezhilarasie, S. Kanimozhi Suguna, and A. Umamakeswari,2015), eye-tracking to detect driver fatigue (2011).

Template matching is a method for discovering zones of a picture that match to a format picture. There are two picture classifications the source picture the picture in which we hope to discover a match to the format picture and the Template picture the patch picture which will be contrasted with the format picture. To recognize the matching territory, must be contrasting the format picture against the picture by sliding. Sliding is moving the patch one pixel at once (left to right, up to down). At every area, a metric is computed. So it represents how “Great” or “Terrible” the match at that area is (or how comparable the patch is in that specific territory of the source picture). The brightest areas indicate the highest matches.

Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) for Blink Detection, J. Lee, H. Jung, K.R. Park and J. Kim propose another driver checking system considering driver tiredness and diversion. In the event that the driver is looking ahead, tiredness identification is performed. If not diversion discovery is performed. Besides, another eye recognition, calculation is presented. It joins versatile boosting, versatile layout matching, and blob discovery with eye acceptance. Those calculations diminish the eye discovery lapse and handling time essentially, by accomplished the said calculations. Third, they have used principal component analysis (PCA), and linear discriminate analysis (LDA) with a specific end goal to attain exact eye identification. Fourth, they have proposed a novel eye state detection calculation that joins appearances gimmicks got utilizing PCA and LDA, with measurable peculiarities.

Harr cascade Classifier, J. Suryaprasad classifies the method for face/eye detection methods utilizing image processing in real time. In this project, it further clarifies the method for utilizing the harr cascade tests and the separation of eye blink and drowsiness identification. This paper acquaints a vision based strategy with distinguishing the drowsiness. The significant difficulties are face recognition, Iris location under different conditions and creating the real time system.

Cascaded regression method estimates the face shape through a cascade of regressors. It starts from a raw initial guess of landmark positions and learns regressors that iteratively map shape-dependent features into shape increment. Examples of cascaded regression algorithms include the approach by Cristinacce and Cootes which employs boosted regression for facial landmarks alignment. Xiong and De la Torre propose a Supervised Descent Method (SDM) which learns descent directions and does linear mapping on non-linear SIFT features. Cao et al use pixel differences as features and implement nonlinear boosted regression. Burgos-Artizzu et al build a cascaded regression model with occlusion detection and voting strategy to cope with severe occlusion. Regression forest voting for accurate shape fitting was proposed by Cootes et al. Random forests and random ferns are frequently used in recent research papers as the regression algorithms.

In June, 2010, Bin Yang et. al. [16] described ‘Camerabased Drowsiness Reference for Driver State Classification under Real Driving Conditions’. They proposed that measures of the driver’s eyes are capable to detect drowsiness under simulator or experiment conditions. The performance of the latest eye tracking based in-vehicle fatigue prediction measures are evaluated. These measures are assessed statistically and by a classification method based on a large dataset of 90 hours of real road drives. The results show that eye-tracking drowsiness detection works well for some drivers as long as the blinks detection works properly. Even with some proposed improvements, however, there are still problems with bad light conditions and for persons wearing glasses. As a summary, the camera based sleepiness measures provide a valuable contribution for a drowsiness reference, but are not reliable enough to be the only reference.

In featured based algorithms the features required are isolated from the entire image. This has an advantage of low computing resources. On the other hand, model-based approaches do not explicitly detect features but rather find the best fitting model that is consistent with the image.

Dongheng Li, Derick J. Parkhrust [4] has discussed that Starburst algorithm is a robust eye-tracking algorithm that combines feature-based and model-based approaches to achieve a good trade-off between run-time performance and accuracy for dark-pupil infrared imagery. The goal of the algorithm is to extract the location of the pupil center and the corneal reflection so as to relate the vector difference between these measures to coordinates in the scene image. The algorithm begins by locating and removing the corneal reflection from the image. Then the pupil edge points are located using an iterative feature-based technique. An ellipse is fitted to a subset of the detected edge points using the Random Sample Consensus (RANSAC). The best fitting parameters from this feature-based approach are then used to initialize a local model-based search for the ellipse parameters that maximizes the fit to the image data.

In 2008, Hong Su et. al. [15] described ‘A Partial Least Squares Regression-Based Fusion Model for Predicting the Trend in Drowsiness’. They proposed a new technique of modeling driver drowsiness with multiple eyelid movement features based on an information fusion technique—partial least squares regression (PLSR), with which to cope with the problem of strong collinear relations among eyelid movement features and, thus, predicting the tendency of the drowsiness. The predictive precision and robustness of the model thus established are validated, which show that it provides a novel way of fusing multi-features together for enhancing our capability of detecting and predicting the state of drowsiness.

In 2011, M.J. Flores et. al. [17] described ‘Driver drowsiness detection system under infrared illumination for an intelligent vehicle’. They proposed that to reduce the amount of such fatalities, a module for an advanced driver assistance system, which caters for automatic driver drowsiness detection and also driver distraction, is presented. Artificial intelligence algorithms are used to process the visual information in order to locate, track and analyze both the driver’s face and eyes to compute the drowsiness and distraction indexes. This realtime system works during nocturnal conditions as a result of a near-infrared lighting system. Finally, examples of different driver images taken in a real vehicle at nighttime are shown to validate the proposed algorithms.

In June, 2012, A. Cheng et. al. [18] described 'Driver Drowsiness Recognition Based on Computer Vision Technology’. They presented a nonintrusive drowsiness recognition method using eye-tracking and image processing. A robust eye detection algorithm is introduced to address the problems caused by changes in illumination and driver posture. Six measures are calculated with percentage of eyelid closure, maximum closure duration, blink frequency, average opening level of the eyes, opening velocity of the eyes, and closing velocity of the eyes. These measures are combined using Fisher’s linear discriminated functions using a stepwise method to reduce the correlations and extract an independent index. Results with six participants in driving simulator experiments demonstrate the feasibility of this video-based drowsiness recognition method that provided 86% accuracy.

In 2013, G. Kong et. al. [19] described ‘Visual Analysis of Eye State and Head Pose for Driver Alertness Monitoring’. They presented visual analysis of eye state and head pose (HP) for continuous monitoring of alertness of a vehicle driver. Most existing approaches to visual detection of non-alert driving patterns rely either on eye closure or head nodding angles to determine the driver drowsiness or distraction level. The proposed scheme uses visual features such as eye index (EI), pupil activity (PA), and HP to extract critical information on non-alertness of a vehicle driver. A support vector machine (SVM) classifies a sequence of video segments into alert or non-alert driving events. Experimental results show that the proposed scheme offers high classification accuracy with acceptably low errors and false alarms for people of various ethnicity and gender in real road driving conditions.

In June, 2014, Eyosiyas et. al. [20] described ‘Driver Drowsiness Detection through \HMM based Dynamic Modeling’. They proposed a new method of analyzing the facial expression of the driver through Hidden Markov Model (HMM) based dynamic modeling to detect drowsiness. They have implemented the algorithm using a simulated driving setup. Experimental results verified the effectiveness of the proposed method.

In August 2014, García et. al. [21] described ‘Driver Monitoring Based on Low-Cost 3-D Sensors’. They proposed a solution for driver monitoring and event detection based on 3-D information from a range camera is presented. The system combines 2-D and 3-D techniques to provide head pose estimation and regions-of-interest identification. Based on the captured cloud of 3-D points from the sensor and analyzing the 2-D projection, the points corresponding to the head are determined and extracted for further analysis. Later, head pose estimation with three degrees of freedom (Euler angles) is estimated based on the iterative closest points algorithm. Finally, relevant regions of the face are identified and used for further analysis, e.g., event detection and behavior analysis. The resulting application is a 3-D driver monitoring system based on low-cost sensors. It represents an interesting tool for human factor research studies, allowing automatic study of specific factors and the detection of special event related to the driver, e.g., driver drowsiness, inattention, or head pose.

Robert Gabriel Lupu [3] has discussed that in the previous year’s many algorithms for eye pupil/iris detection have been developed. Depending upon the source light point of view there are two approaches namely based on ambient or infrared light. All of them search for characteristics of the eye. There are some algorithms that search for features like blackest pixels in the image, pixels that correspond to pupil or iris and are known as feature based algorithms. Other algorithms are trying to best fit a model to the pupil/iris contour and are known as model based algorithms. In featured based algorithms the features required are isolated from the entire image. This has an advantage of low computing resources. On the other hand, model-based approaches do not explicitly detect features but rather find the best fitting model that is consistent with the image. Dongheng Li, Derick J. Parkhrust [4] has discussed that Starburst algorithm is a robust eye-tracking algorithm that combines feature-based and model-based approaches to achieve a good trade-off between run-time performance and accuracy for dark-pupil infrared imagery. The goal of the algorithm is to extract the location of the pupil center and the corneal reflection so as to relate the vector difference between these measures to coordinates in the scene image. The algorithm begins by locating and removing the corneal reflection from the image. Then the pupil edge points are located using an iterative feature-based technique. An ellipse is fitted to a subset of the detected edge points using the Random Sample Consensus (RANSAC). The best fitting parameters from this feature-based approach are then used to initialize a local model-based search for the ellipse parameters that maximizes the fit to the image data. Robert Gabriel Lupu [3] has discussed that, The ETAR algorithm has a feature based approaches. It starts by searching the region where the eye is located, using HaarCascadeFilter. The region is set as region so interest (ROI) and a mask image is constructed in order to eliminate the unwanted noise from the four corners of ROI. The algorithm continues with determination of an optimal binary segmentation threshold. The pupil centre is determined by applying the center of mass to the group of pixels that correspond to the pupil from the segmented ROI image. The analysis of determined gaze direction reveals that the algorithm is not sensitive to the noise from the image.

The Author Jayasenan J. S and Mrs. Smitha P. S in their paper explained four methods to detect drowsiness: (1) sensing of physiological characteristics, (2) sensing of driver operation, (3) sensing of vehicle response, (4) monitoring the response of driver.[1] Out of this, the first two methods are accurate but expensive and need many sensors like brainwave sensor which cannot be used. Whereas, methods like sensing vehicle responses and monitoring the driver responses is a good method and implementable. Author Mrs.S. Dhanalakshmi, J.Jasmine Rosepet, G.Leema Rosy, M.Philominal said in their paper that machine is an important part to detect the face and localize the eyes, but it is more important to train the machine efficiently to work effectively to detect the eyes and drowsiness. Non-intrusive machine vision based drowsy driver detection system in which images are used to detect eye position and eye blinking and eye blink frequency to calculate drowsiness detection [4] can work perfectly and can save the lives of many people. Various papers show that using SVM can make the system robust but increases complexity of the system.

Many researchers consider the subsequent physiological signals to observe drowsiness, electrocardiogram (ECG), electro encephalogram (EEG). The heart rate (HR) additionally varies considerably between the different stage of drowsiness, like alertness and fatigue. Therefore, heart rate, which may be simply determined by the ECG signal, can even be used to observe drowsiness. Others have measured drowsiness using heart rate variability (HRV), within which the low (LF) and high (HF) frequencies fall within the range of 0.04-0.15 Hertz and 0.14-0.4 Hertz respectively, shows a physiological signal sensing system that may be integrated into vehicles to observe driver drowsiness. But still, compared to the drowsiness detection using behavioral measures, numbers of researches on physiological measures to detect drowsiness are low.

**2.3. Summary**

Several techniques can be applied in the driver’s drowsiness such as Template Matching, Harr cascade, Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA), Deep Neural Networks. But, these techniques have disadvantages such as performance, resources sharing and accuracy. Thus, a system is proposed that detects driver’s drowsiness using EAR (Eye Aspect Ratio) and ERT (Ensemble of Regression Tree).