

# Experimental Study on Assessment on Impact of Biometric Parameters on Drowsiness Detection



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**Abstract :** Working in monotonous environment like vehicle driving, operating a machine for a long time often causes drowsiness leading to fatal accidents. Therefore early detection of fatigued state has become necessary to develop the detection system. In this paper, detection of drowsiness based on biometric parameters like eyelid movement and eyebrow is proposed. Experiment was conducted on sample size of 50 video clips and observed that eyelid movement contributes about 50% and eyebrow contributes about 5%.

**Key words :** Biometric parameters, Drowsiness detection, Haarcascade classifiers, Support Vector Machine (SVM).

## INTRODUCTION

The ever-increasing number of accidents that are due to a diminished human vigilance level which has become a problem of serious concern to society. Person with a diminished vigilance level suffer from a marked decline in their perception, recognition, and machine/vehicle-control abilities and, therefore, pose a serious danger to their own life and the lives of other people.

Statistics show that a leading cause of fatal or injury-causing accidents is due to person with a diminished vigilance level which is due to the working of a person or operator in a monotonous environment which often causes lack of concentration of fatigue in an operator and many times such non-vigilance leads to accidents. Apart from fatigue, non vigilance can be also caused by certain mental states like anger, frustration, excitation or being uncomfortable with the environment; which in turn lead to decreased vigilance.

In truck industry [9], about 60% of accidents are related to driver fatigue. It is the number one cause of heavy truck crashes. Seventy percent of drivers report driving fatigued. Monitoring the driver's level of vigilance and alerting the driver when he is not paying adequate attention to the road has become essential in order to prevent accidents. Detection of driver's visual attention is very important for developing automatic systems that monitor the driver's inattention, driver fatigue, and lack of sleep. A great number of fatalities occurring in motor vehicles could be avoided if these behaviours were detected.

With the ever-growing traffic conditions, this problem will further increase. For this reason developing a system that actively monitoring a driver's level of vigilance and alerting the driver of any insecure driving conditions is essential for accident prevention. Many efforts have been reported in the literature for developing an active safety system for reducing the number of automobile accidents due to reduced vigilance. Many times in listening lectures or attending meetings become monotonous & symptoms of drowsiness can be clearly seen in vigilance.

Possible techniques for detection of drowsiness can be classified into 3 major categories physiological, behavioural & visual measures [9].

- a. Physiological measures: It is done by measuring changes in physiological signals, such as brain waves and heart rate. This technique is most accurate, is not realistic since sensing electrodes would have to be attached directly onto the person's body, and hence be annoying and distracting to the driver. In addition, long time driving would result in perspiration on the sensors, diminishing their ability to monitor accurately.
- b. Behavioural measures: These are also accurate and objective. This category of devices, most commonly known as acti-graph, is used to measure sleep based on the frequency of body movement. The number of body movement recorded during a specified time period, or epoch, has been found to significantly correlate with the presence of sleep and has a significant correlation with EEG.
- c. Visual measures: An increasing research interest has focused on developing systems that detect the visual facial feature changes associated with fatigue with a video camera. These facial features include eyes, head position, face, or mouth. This approach is non-intrusive and becomes more and more practical with the rapid development of camera and computer vision technology.

The paper is organized into 5 sections as: Previous study of detection of fatigueness by different researchers is reviewed in Section 2 & system architecture of proposed system is discussed in section 3; Section 4 shows the various experimental results carried out and finally paper is concluded in section 5.

## PREVIOUS WORKS

Many efforts on developing active real-time image-based fatigue- monitoring systems have been reported in the literature. These efforts are primarily focused on detecting driver fatigue from facial expression or line of sight or eyelid movement or physiological signals.

In [1], this paper author says, a probabilistic framework based on the BN to model fatigue, the associated factors, and the sensory observations in a principled way is proposed. Specifically, a static fatigue model based on the static BN model was developed to model the static aspects of fatigue and to allow integration of the relevant contextual information and the available sensory data spatially. The static fatigue model is then extended based on DBNs to better model the dynamic and evolutionary aspects of fatigue development. Experimental results involving both synthetic and real data demonstrate the validity of the proposed fatigue model in modeling and real-time inferring fatigue based on simultaneous combination of various parameters over time and under uncertainty. The framework allows is to perform fatigue inference over time and under uncertainty.

In [2], this paper authors presents a nonintrusive prototype computer vision system for monitoring a driver's vigilance in real time. It is based on a hardware system for a real-time acquisition of driver's images using an active IR illuminator and the implementation of software algorithms for the real-time monitoring of six parameters are calculated: Percent eye closure (PERCLOS), eye closure duration, blink frequency, nodding frequency, face position, and fixed gaze. These parameters are combined using a fuzzy classifier to infer the level of inattentiveness of the driver. The system works robustly at night and for users not wearing glasses, yielding an accuracy percentage close to 100%. The performance of the system decreases during daytime, especially in bright days, and at the moment, the system does not work with drivers wearing glasses.

In [3], this paper authors says study, proposed a driver-monitoring system that can be used for warning against driver inattention, including drowsiness and distraction. They proposed an algorithm that automatically localizes the eyes, determines whether they are opened or closed, and finally judges whether the driver is driving drowsily or distractedly. In this process, two measures, PERCLOS and PERLOOK, are used to calculate the drowsiness and distraction levels, respectively, and they yield satisfactory results. This constitutes a nonintrusive approach to detecting driver inattention without annoyance or interference in both daytime and night time. This system will exhibit better performance if it is integrated with other sensors, such as the accelerator, steering wheel, and lane-position sensor. Finally, an integrated driving safety system will be more effective when combined with a pedestrian-recognition system and a lane-keeping support system.

In [4], this paper the authors have worked on the video files recorded by the camera. Video file is converted into frames. Once the eyes are located from each frame, by

determining the energy value of each frame one can determine whether the eyes are open or close. A particular condition is set for the energy values of open and close eyes. If the average of the energy value for 5 consecutive frames falls in a given condition then the driver will be detected as drowsy and issues a warning signal. A non-invasive system to localize the eyes and monitor fatigue was developed. Information about the eyes position is obtained through various self-developed image processing algorithms. During the monitoring, the system is able to decide if the eyes are open or closed. When the eyes have been closed for too long, a warning signal is issued.

In [6], this paper, authors propose a dynamic clustering method based on EEG to estimate vigilance states. This method uses temporal series information to supervise EEG data clustering, which is used for the case that the labeled data are poor and limited. So authors consider the gradually changing characteristic of vigilance state transition, the proposed dynamic clustering algorithm utilizes the neighborhood information to improve the clustering performance, and can obtain a reasonable grouping of the EEG data at 2 seconds temporal resolution.

In [8], this paper authors says, according to novel algorithm to detect drowsiness based on multidimensional biometric features like mouth geometrical features and eyelid movement is proposed. The three parameters of the eye such as duration of closure, duration of opening and frequency of blink is used to check for drowsiness based on eyelid movement. The processing is done only on one of the eye, thus to increase speed of detection and to detect under different hair style conditions. The algorithm fails to detect drowsiness under few adverse conditions such as different skin colors, wearing spectacles and any lighting conditions.

In [9], this paper author attempts to present a comprehensive survey of reviews and compares current status of research in modeling fatigue where fatigue is modeled using probabilistic models, machine learning models, finite state machine etc. The paper also presents possible future research directions in the same field like identifying non-fatigue non-vigilance mental states, extending non-vigilance monitoring for mass audience etc research on driver fatigue detection and to provide some structural categories for the methods.. The fatigue monitoring devices have to be more accurate than drivers' own self reports if they are going to be used in vehicles to improve driving safety. If drivers learn to rely on the technology for they believe it is accurate, then the failure of warning may be a catastrophe for drivers. If the driver believe that the device is misleading them it will be ignored totally, even if an unsafe fatigue is detected, which also can cause an accident. Furthermore, he says if the warning occurs early enough in the development of fatigue, such devices can enhance driver alertness sufficient to avoid a collision, although many of the devices currently under development. Some of the problems with the fatigue detection systems currently under development include the stage of drowsiness being detected and the combination of different measures.

In [10], this paper authors describes a method to monitor driver safety by analyzing information related to fatigue using two distinct methods: eye movement monitoring and bio-signal processing, a fatigue monitoring system focused on information fusion is designed and implemented in Android-based smart phone. The final output of the system defining the driver status at a specific time is estimated with a dynamic Bayesian network paradigm. A warning alarm is sounded if driver fatigue is believed to reach a defined threshold. The studies revealed that adoption of more information in fatigue detection; the higher degree of performance can be achieved instead of performing statistical analysis based on single information. In our studies, the information used is mainly the facial expression and physiological data of the driver.

In [11], this paper authors says, a new method for inferring driver's fatigue estimation based on the dynamic Bayesian network was proposed. Multiple features, including contextual, contact physiological, and contactless physiological features were used, which have the widest coverage of the categories of features. The first-order Hidden Markov Model (HMM) has been employed to compute the dynamics of a Bayesian network at two different time slices. Simulation-based experiments were performed to demonstrate the validation of the proposed model. Two important conclusions can be drawn from this study: (I) more features, especially the contact physiological feature category, which covers more features implying driver fatigue recognition, are favorable for inferring the driver fatigue more reliably and accurately; (ii) the ECG and EEG are two important features for fatigue recognition, and they should not be absent from consideration in any driver fatigue detection system. It would be of significant interest to extend the current model of a discrete random process to a continuous random process to handle more practical situations.

In [12], this paper authors presents a system for automatic detection of driver drowsiness from video. Previous approaches focused on assumptions about behaviours that might be predictive of drowsiness. Here, a system for automatically measuring facial expressions was employed to data mine spontaneous behaviour during real drowsiness episodes. This work to knowledge to reveal significant associations between facial expression and fatigue beyond eye blinks. It also revealed a potential association between head roll and driver drowsiness, and the coupling of head roll with steering motion during drowsiness. Of note is that a behaviour that is often assumed to be predictive of drowsiness, yawn, was in fact a negative predictor of the 60-second window prior to a crash. It appears that in the moments before falling asleep, drivers yawn less, not more, often. The system was able to predict sleep and crash episodes during a driving computer game with 96% accuracy within subjects and above 90% accuracy across subjects. This is the highest prediction rate reported to date for detecting real drowsiness.

## PROPOSED METHOD

This paper focuses on the development on drowsiness detection system based on the biometric parameters like eyelid movement and eyebrow on human fatigue under different adverse conditions over timeline which results the analysis of the state of drowsiness level. This paper is implemented in JavaCV (Java Computer Vision).

The general architecture of our system is show in fig 1, which consists of 5 major modules:

- Data collection
- Face detection
- Eye detection
- Visual behaviour (Eyelid movement & eye brow tracking)
- Vigilance level

The sample videos are collected with different intensities or captured using webcam for fixed interval of time. The face region is detected from the videos after being framed using Viola-Jones algorithm. After detecting the face, eye regions of the face is detected using haar cascade classifier and processed to detect the level of drowsiness using support vector machine technique as shown in fig 1.

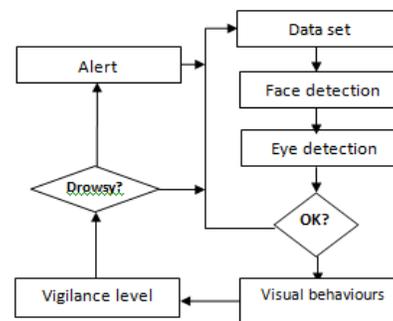


Fig 1: General Architecture

## Face detection

In this stage the collected videos are processed further into frames for face detection, Viola-Jones [5] classifier is used with haarcascade classifier to detect face. Once the face region is detected it is marked the rectangle as shown in fig 2. Viola-Jones [5] face detection framework is capable of processing images extremely while achieving high detection rates as the process of training is simple and efficient. This classifier can be used as a “supervised” focus for attention of operator and they present a set of experiments in the domain of face detection.

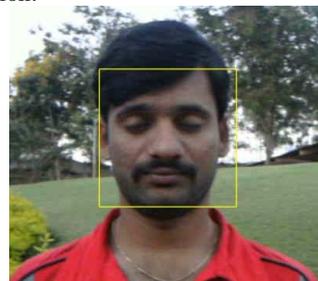


Fig 1: Detected face

### Eye detection

Once the face region is detected, the eyes are detected using Haarcascade classifiers [5] [13]. The classifier uses the Haar-like features. The object detector puts the list of detected eye and the rectangle is drawn for the eye region of the face as shown in fig 3.

Even this approach [8] can be done using single eye detection as in fig 4, which can be used for the different conditions where the eye is partially covered with hairs. Eye blinking (eye lid movement) is monitored continuously by observing the status of the eye such as open or closed in each frame. In closed state, eye is not detected and is detected only in the open state. Normally, the eye blinks 10 times per minute, the interval is about two to six seconds, and the duration of each blink is about 0.15 to 0.25 seconds [8]. If eye is closed for more than 8 frames then the person is in fatigue. When a person is drowsy the frequency of his eye blink becomes slower. Contrarily, when he just becomes drowsy from normal spirit state, the frequency of his eye blink is faster during the conversion stage. If the person feels drowsy, to avoid this, he tries to keep his eye open for longer duration. If eye blink of a person is continuous with more frequency, that is if it is larger than 10 times per minute then he is in a fatigue state and he is alarmed. After detection of face and eye, eyebrows are also located and marked with the rectangles. When the person is tired his eye blinking frequency may be faster, at the same time the position of eyebrow is raised/lowered. By tracking the position of the eyebrow we can say that the eye brow contributes for the detection of fatigue.

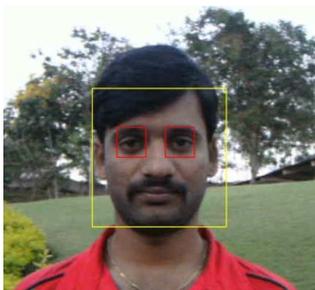


Fig 3: Detection of both eyes;

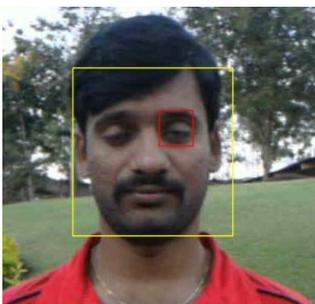


Fig 4: Detection of single eye

The algorithm to detect the drowsy is described below:

Procedure drowsy\_detection

1. Retrieve/record the video clip using database/webcam (offline/online).

2. Processing the video clip into frames.
  3. Detect face using Haarcascade classifier.
  4. Detect eye using Haarcascade classifier.
  5. Extraction of the features of eye parameters like eyelid movement and eyebrow.
  6. SVM function is called to find whether drowsy or not.
- End of procedure.

Firstly the videos are captured from webcam then stored frame by frame. Face is detected using Viola Jones classifier, then using haarcascade classifier eye located and a rectangle is drawn around them. Then the eye opens and closes are calculated for each frame and counted. Then the frequency blink is calculated for each person. Also the eyebrow position is detected as the normal position and abnormal position. The extracted parameters eye closure, eye opens, frequency blinks and eye brow positions are given as input for machine learning technique called Support Vector Machine (SVM) to identify the drowsiness. The complete process of drowsiness detection is explained using flow diagram as shown in fig 5.

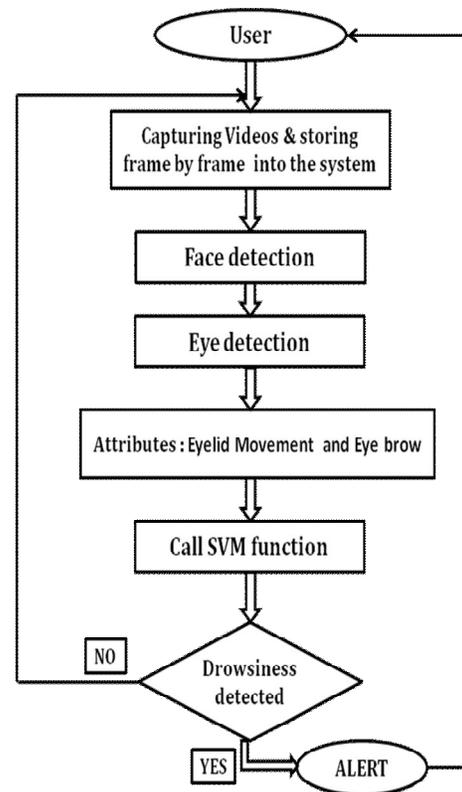


Fig 5: Flow diagram

### EXPERIMENTAL RESULTS

Around 100 videos were collected of different facial attributes like with spectacles, without spectacles, different hair style conditions, with beard and without beard in different adverse conditions over timeline. Some of the experimented results of video clips are listed in table 1.

Table 1: Experimental Results of Drowsiness Detection

No.	Time	EC	EO	FB	EB	Drowsy
1	10.0	10.0	8.0	8.0	T	N
2	5.0	1.0	3.0	8.0	F	Y
3	10.0	5.0	4.0	8.0	F	N
4	16.0	4.0	2.0	8.0	T	Y
5	10.0	3.0	1.0	8.0	F	N
6	3.0	20.0	4.0	8.0	T	Y
7	10.0	10.0	8.0	8.0	T	N
8	5.0	1.0	3.0	8.0	F	Y
9	10.0	5.0	4.0	8.0	F	N
10	16.0	4.0	2.0	8.0	T	Y
11	10.0	3.0	1.0	8.0	F	N
12	8.0	6.0	7.0	8.0	T	Y
13	10.0	8.0	0.0	8.0	F	N
14	1.0	10.0	8.0	8.0	F	Y
15	10.0	4.0	1.0	8.0	F	N
16	3.0	3.0	1.0	8.0	F	Y
17	16.0	4.0	2.0	8.0	T	Y
18	10.0	3.0	1.0	8.0	F	N
19	5.0	10.0	5.0	8.0	F	N
20	8.0	6.0	7.0	8.0	T	Y
21	10.0	8.0	0.0	8.0	F	N
22	1.0	10.0	8.0	8.0	F	Y
23	10.0	10.0	8.0	8.0	T	N
24	5.0	1.0	3.0	8.0	F	Y
25	10.0	5.0	4.0	8.0	F	N
26	16.0	4.0	2.0	8.0	T	Y
27	10.0	3.0	1.0	8.0	F	N
28	5.0	10.0	5.0	8.0	F	N
29	8.0	6.0	7.0	8.0	T	Y
30	10.0	8.0	0.0	8.0	F	N
31	1.0	10.0	8.0	8.0	F	Y
32	10.0	4.0	1.0	8.0	F	N
33	3.0	3.0	1.0	8.0	F	Y
34	10.0	4.0	1.0	8.0	F	N
35	3.0	3.0	1.0	8.0	F	Y
36	10.0	10.0	8.0	8.0	T	N
37	5.0	1.0	3.0	8.0	F	Y
38	8.0	6.0	7.0	8.0	T	Y
39	2.0	7.0	1.0	8.0	T	Y
40	10.0	6.0	2.0	8.0	F	Y
41	4.0	9.0	3.0	8.0	T	Y
42	10.0	7.0	2.0	8.0	F	Y
43	10.0	8.0	0.0	8.0	F	N
44	1.0	10.0	8.0	8.0	F	Y
45	8.0	6.0	7.0	8.0	T	Y
46	2.0	7.0	1.0	8.0	T	Y
47	10.0	6.0	2.0	8.0	F	Y
48	4.0	9.0	3.0	8.0	T	Y
49	10.0	7.0	2.0	8.0	F	Y
50	10.0	8.0	0.0	8.0	F	N
51	1.0	10.0	8.0	8.0	F	Y
52	10.0	10.0	8.0	8.0	T	N
53	5.0	1.0	3.0	8.0	F	Y
54	10.0	10.0	8.0	8.0	T	N
55	5.0	1.0	3.0	8.0	F	Y
56	8.0	6.0	7.0	8.0	T	Y
57	2.0	7.0	1.0	8.0	T	Y
58	10.0	6.0	2.0	8.0	F	Y
59	4.0	9.0	3.0	8.0	T	Y
60	10.0	7.0	2.0	8.0	F	Y
61	10.0	8.0	0.0	8.0	F	N
62	10.0	4.0	1.0	8.0	F	N
63	3.0	3.0	1.0	8.0	F	Y
64	10.0	4.0	1.0	8.0	F	N
65	3.0	3.0	1.0	8.0	F	Y
66	10.0	10.0	8.0	8.0	T	N
67	5.0	1.0	3.0	8.0	F	Y
68	8.0	6.0	7.0	8.0	T	Y
69	2.0	7.0	1.0	8.0	T	Y
70	10.0	6.0	2.0	8.0	F	Y
71	4.0	9.0	3.0	8.0	T	Y

72	10.0	7.0	2.0	8.0	F	Y
73	10.0	8.0	0.0	8.0	F	N
74	1.0	10.0	8.0	8.0	F	Y
75	10.0	10.0	8.0	8.0	T	N
76	5.0	1.0	3.0	8.0	F	Y
77	10.0	4.0	1.0	8.0	F	N
78	3.0	3.0	1.0	8.0	F	Y
79	10.0	5.0	4.0	8.0	F	N
80	4.0	9.0	3.0	8.0	T	Y
81	10.0	7.0	2.0	8.0	F	Y
82	10.0	8.0	0.0	8.0	F	N
83	10.0	4.0	1.0	8.0	F	N
84	3.0	3.0	1.0	8.0	F	Y
85	10.0	5.0	4.0	8.0	F	N
86	16.0	4.0	2.0	8.0	T	Y
87	10.0	3.0	1.0	8.0	F	N
88	5.0	10.0	5.0	8.0	F	N
89	8.0	6.0	7.0	8.0	T	Y
90	2.0	7.0	1.0	8.0	T	Y
91	10.0	6.0	2.0	8.0	F	Y
92	4.0	9.0	3.0	8.0	T	Y
93	10.0	7.0	2.0	8.0	F	Y
94	10.0	8.0	0.0	8.0	F	N
95	1.0	10.0	8.0	8.0	F	Y
96	10.0	4.0	1.0	8.0	F	N
97	3.0	3.0	1.0	8.0	F	Y
98	6.0	12.0	1.0	8.0	F	N
99	16.0	4.0	2.0	8.0	T	Y
100	10.0	3.0	1.0	8.0	F	N

**Time:** Duration of video clip

**EC:** Eye close in Continuous frame

**EO:** Eye opens in Continuous frame

**FB:** Frequency of eye blink

**EB:** Position of eye brow (normal/abnormal).

In the experimentation we have used around 135 videos, which resulted in 70% of drowsiness detected. In which eyelid movement has impact of 50% and eyebrow position has very less impact of 5%. In this experiment we considered the duration of video clips, in which the number of eye open and closes are calculated by counting the continuous frames. In this paper eye is detected even in the adverse conditions also such as with spectacles, without spectacles, different hair style conditions. In general the minimum blink rate of eye is 10 blinks per minute. If eye is closed for more than 8 frames then the person is in fatigue. Even the position of eye brow is calculated in two stages i.e., normal and above normal. If the position of eyebrow is above normal then the person is fatigue else not. Based on the all the parameters we consider the drowsiness of the person.

Based on the results of detection of drowsiness graph is plotted as shown in fig 6. Where blue color indicates the drowsiness is detected and red indicates not.

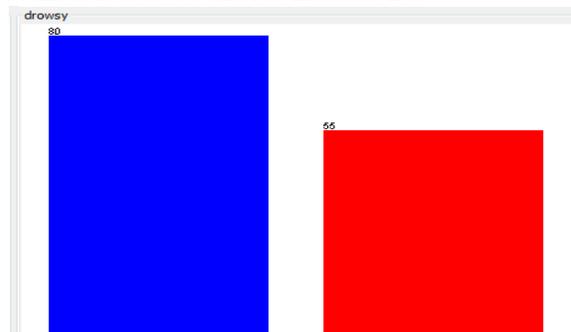


Fig 6: Graph of drowsiness detection

Based on the results of detection of eye open & close is plotted as shown in fig 7. Where blue color indicates the eye close in continuous frames and red indicates open.

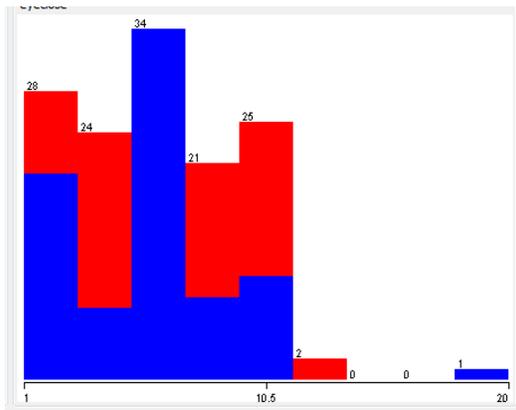


Fig 7: Graph of eye open/close

Based on the results of detection of position of eyebrow is plotted as shown in fig 8. Where blue color indicates the normal position and red indicates above normal position.

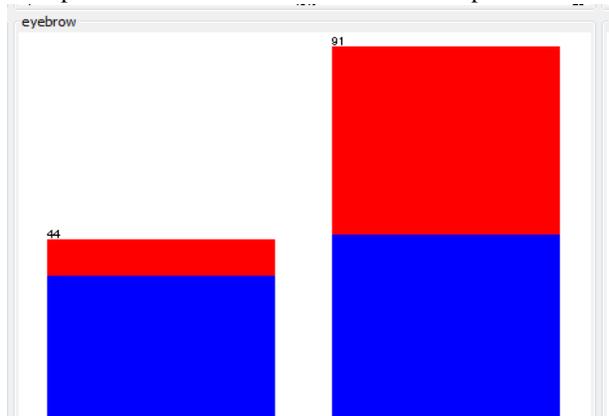


Fig 8: Graph of eyebrow position

## CONCLUSION

In this paper, we have developed the drowsiness detection subsystem based on biometric features like eyelid movement and eyebrow. The parameters of eye like blink rate and position of eyebrow is used to check for drowsiness based on eyelid movement and eyebrow. The processing is done under different adverse condition like hair style conditions, wearing spectacle or not wearing, with beard or without. The algorithm works satisfactory under reasonable lighting conditions and fails to detect under very dark. The algorithm fails to detect drowsiness under few conditions such as different skin colors.

## ACKNOWLEDGEMENT

This project was carried under Research Promotion Scheme grant from All India Council for Technical Education (AICTE), project Ref. No: 8023/RID/RPS-114(Pvt)/ 2011-12. Authors wish to thank

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