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A Novel Method for Detecting Drowsiness In Real Time

Itenderpal Singh[1], Dr. V.K Banga [2]
M.Tech. Scholar, Dept. of ECE, Amritsar College of Engineering & Technology, Amritsar, India [1]
H.O.D, Dept. of ECE, Amritsar College of Engineering & Technology, Amritsar, India [2]

ABSTRACT---*Driver's drowsiness poses a major threat to roadway safety and can lead to critical physical injuries, deaths and significant economic losses. Statistics indicate the need of a reliable driver drowsiness detection system which could alert the driver before a mishap happens. In this paper, we proposed an algorithm to determine the level of fatigue by measuring the eye opening and closing, and warn the driver accordingly.*
Keywords*: Drowsiness warning system; accidents; face detection; eye detection; neural network*

I. INTRODUCTION

The term "drowsiness" is used here to refer to the state of reduced alertness, usually accompanied by performance and psychophysiological changes that may result in loss of alertness or being "asleep at the wheel." The term "driver fatigue" is also widely used to describe this condition, especially on Police Accident Reports and in accident data files. Due to the increase in the amount of automobile in recent years, problems created by accidents have become more complex as well. Traditional transportation system is no longer sufficient. In recent years, the intelligent vehicle system has emerged and became a popular topic among transportation researchers. However, the research of safety in vehicle is an important subset of intelligent vehicle system research. Meantime, active warning system is one of the designs on active safety system. The safety warning systems, mostly active warning systems for preventing traffic accidents have been attracting much public attention [9]. Safe driving is a major concern of societies all over the world. Thousands of people are killed, or seriously injured due to drivers falling asleep at the wheels each year. Recent studies show those drivers' drowsiness accounts for up to 20% of serious or fatal accidents on motorways and monotonous roads, which impair the drivers' judgment and their ability of controlling vehicles. Therefore, it is essential to develop a real-time safety system for drowsiness-related road accident prevention. Many methods have been developed and some of them are currently being used for detecting the driver's drowsiness, including the measurements of physiological features like EEG, heart rate and pulse rate, eyelid movement, gaze, head movement and behaviors of the vehicle, such as lane deviations and steering movements. Among those different technologies, ocular measures, such as eye-blinking and eyelid closure, are considered as promising ways for monitoring alertness. In this paper the focus will be placed on designing a system that will accurately monitor the open or closed state of the driver's eyes in real-time. By monitoring the eyes, it is believed that the symptoms of driver fatigue can be detected early enough to avoid a car accident.

II. OUR PROPOSED ALGORITHM (FOR TRAINING)

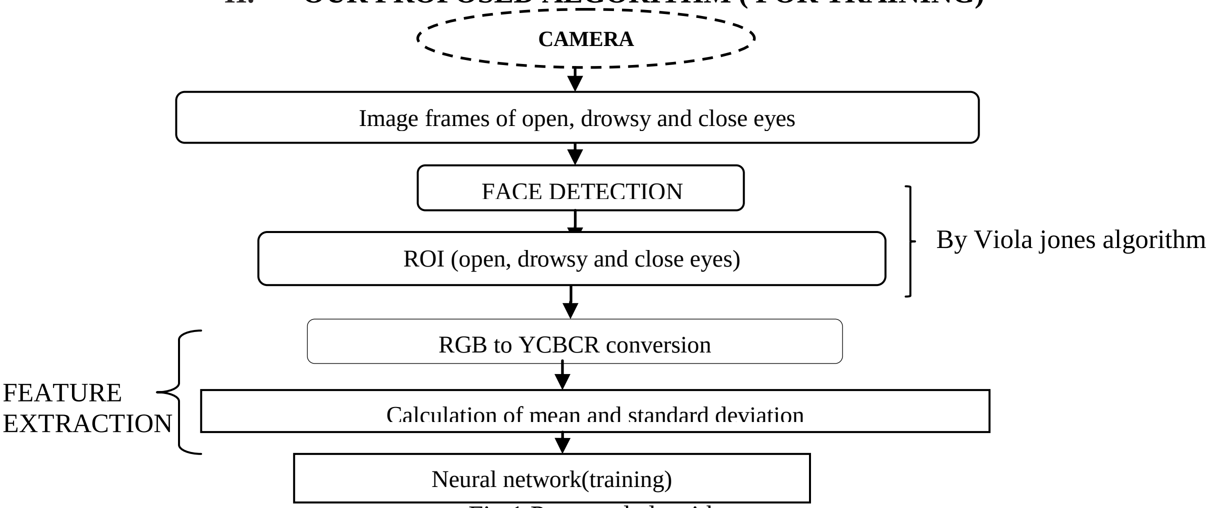


Fig.1 Proposed algorithm

The first step is the image acquisition which is done by using video camera which takes the video of the driver and convert into image frames.

Fig.2 Open, drowsy and close image

The frames of the video are further processed for face detection. In this we use viola jones algorithm to detect face and eyes. Viola-Jones algorithm is based on exploring the input image by means of sub window capable of detecting features. This window is scaled to detect faces of different sizes in the image. Viola Jones developed a scale invariant detector which runs through the image many times, each time with different size. Being scale invariant, the detector requires same number of calculations regardless of the size of the image.

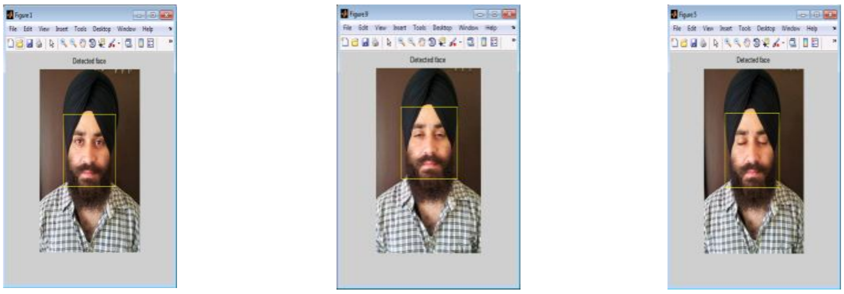


Fig.3 Face detection by viola jones algorithm

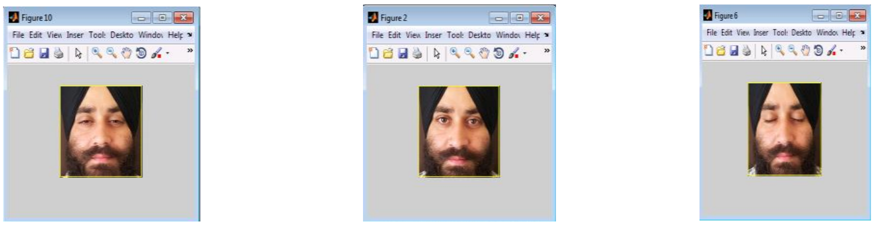


Fig.4 Effect of the background removal on the Image with open, drowsy and close eyes

The third step is eyes detection**;** Similarly, Eyes are detected by using this algorithm. To detect eyes we first detect nose and then detect pair of eyes.

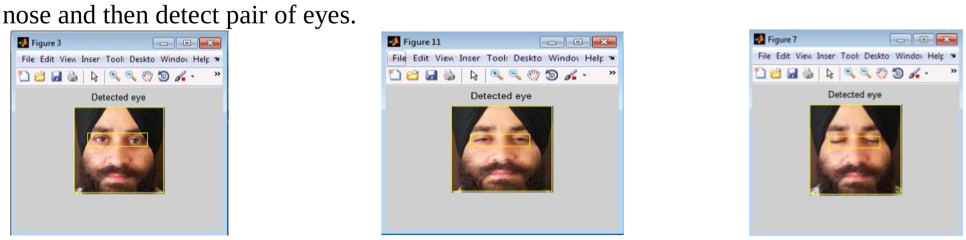


Fig.5 Detected open, drowsy and close eyes.

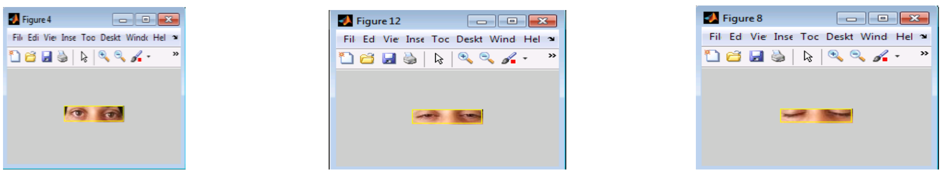


Fig.6 ROI with open, drowsy and close eyes

However, the RGB model includes brightness in addition to the colours. When it comes to human's eyes, different brightness for the same colour means different colour. When analysing a human eye, RGB model is very sensitive in image brightness.

The next step is to extract the features of eyes. i.e. to convert RGB image into YCBCR image: The Cb and Cr components give a good indication on whether a pixel is part of the skin or not. This can clearly be seen in Figure.8, which are the Cb and Cr values of all the pixels that are part of the eye. There is a strong correlation between the Cb and Cr values of skin pixels, to reveal the comparison between eyes and non-eyes in the YCbCr space.

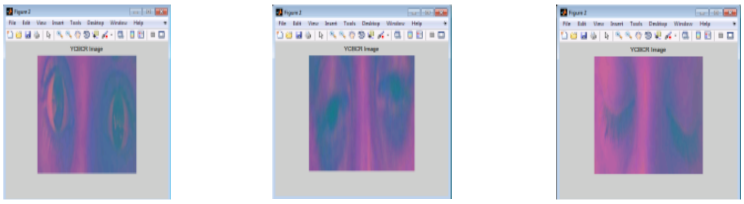


Fig.7 Open, drowsy and close eyes in YCbCr

Therefore, to remove the brightness from the images is second step. We use the YCbCr space since it is widely used in video compression standards, Figure 8. shows the image in YCbCr. Since the skin-tone colour depends on luminance, we nonlinearly transform the YCbCr colour space to make the skin clear. The main advantage of converting the image to the YCbCr domain is that influence of luminosity can be removed during our image processing. In the RGB domain, each component of the picture (red, green and blue) has a different brightness. However, in the YCbCr domain all information about the brightness is given by the Y component, since the Cb (blue) and Cr (red) components are independent from the luminosity.

The next step is to calculate the mean and standard deviation of eyes i.e. for open, drowsy and close image

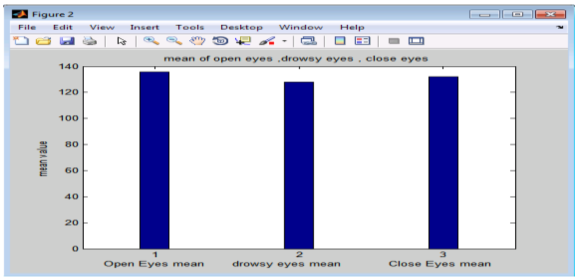


Fig.8 Mean of open, drowsy and close eye.

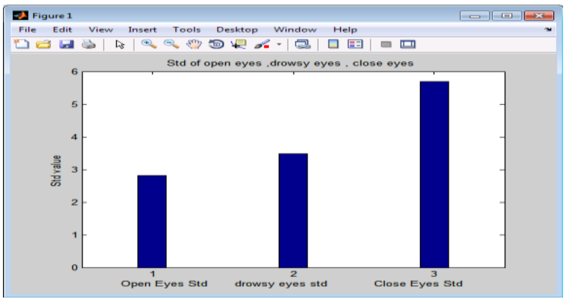


Fig.9 Standard deviation of open, drowsy and close eye.

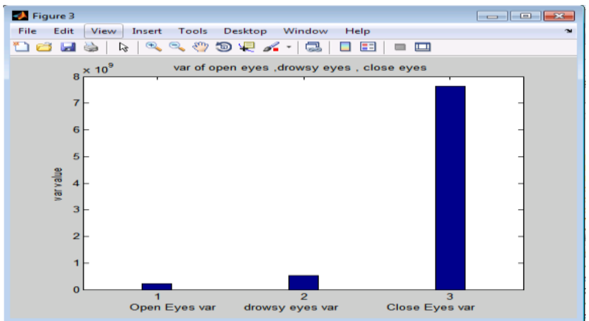


Fig.10 Variance of open, drowsy and close eye.

The above figures are the mean and standard deviation of open, close and drowsy eyes. This is our two parameters which also we are taken to differentiate the open, drowsy and close eyes.

Table A: Target pattern Encoding

S.No	Class	Target Pattern
1	Open(class A)	1 0 0
2	Drowsy(class B)	0 1 0
3	Close(class C)	0 0 1

The last step is to train the network by using back propagation algorithm. Our proposed neural network model is as shown in figure 11.

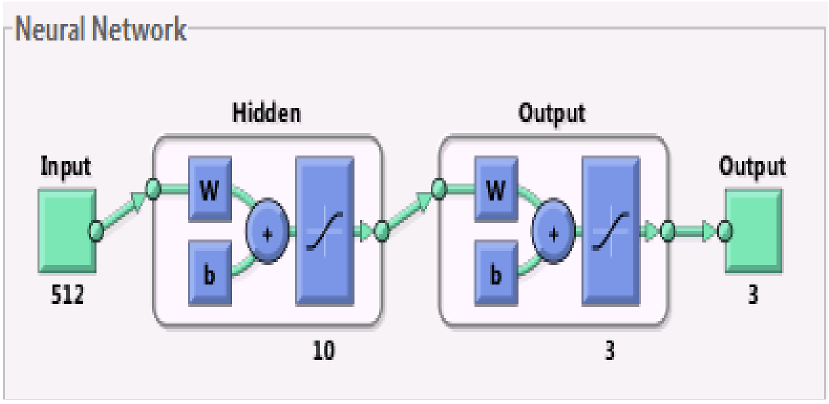
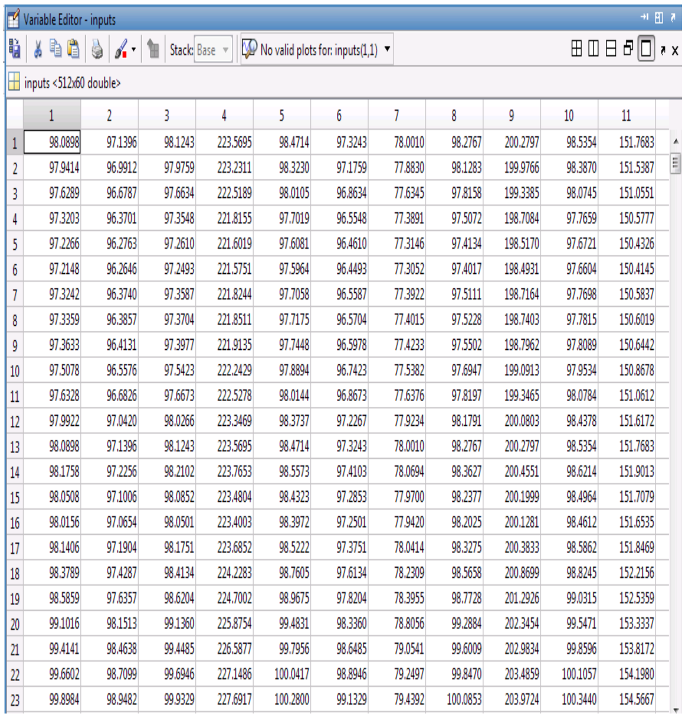


Fig.11 Proposed neural network model

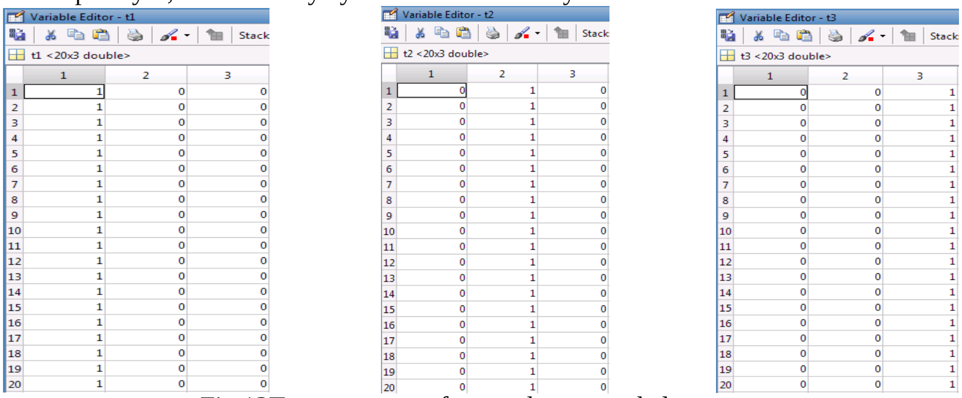
512 at the input nodes represent features of open, drowsy and close eyes and labels at output nodes represent classes.



	1	2	3	4	5	6	7	8	9	10	11
1	98.0898	97.1396	98.1243	223.5695	98.4714	97.3243	78.0010	98.2767	200.2797	98.5354	151.7683
2	97.9414	96.9912	97.9759	223.2311	98.3230	97.1759	77.8830	98.1283	199.9766	98.3870	151.5387
3	97.6289	96.6787	97.6634	222.5189	98.0105	96.8634	77.6345	97.8158	199.3385	98.0745	151.0551
4	97.3203	96.3701	97.3548	221.8155	97.7019	96.5548	77.3891	97.5072	198.7084	97.7659	150.5777
5	97.2266	96.2763	97.2610	221.6019	97.6081	96.4610	77.3146	97.4134	198.5170	97.6721	150.4326
6	97.2148	96.2646	97.2493	221.5751	97.5964	96.4493	77.3052	97.4017	198.4931	97.6604	150.4145
7	97.3242	96.3740	97.3587	221.8244	97.7058	96.5587	77.3922	97.5111	198.7164	97.7698	150.5837
8	97.3359	96.3857	97.3704	221.8511	97.7175	96.5704	77.4015	97.5228	198.7403	97.7815	150.6019
9	97.3633	96.4131	97.3977	221.9135	97.7448	96.5978	77.4233	97.5502	198.7962	97.8089	150.6442
10	97.5078	96.5576	97.5423	222.2429	97.8894	96.7423	77.5382	97.6947	199.0913	97.9534	150.8678
11	97.6328	96.6826	97.6673	222.5278	98.0144	96.8673	77.6376	97.8197	199.3465	98.0784	151.0612
12	97.9922	97.0420	98.0266	223.3469	98.3737	97.2267	77.9234	98.1791	200.0803	98.4378	151.6172
13	98.0898	97.1396	98.1243	223.5695	98.4714	97.3243	78.0010	98.2767	200.2797	98.5354	151.7683
14	98.1758	97.2256	98.2102	223.7653	98.5573	97.4103	78.0694	98.3627	200.4551	98.6214	151.9013
15	98.0508	97.1006	98.0852	223.4804	98.4323	97.2853	77.9700	98.2377	200.1999	98.4964	151.7079
16	98.0156	97.0654	98.0501	223.4003	98.3972	97.2501	77.9420	98.2025	200.1281	98.4612	151.6535
17	98.1406	97.1904	98.1751	223.6852	98.5222	97.3751	78.0414	98.3275	200.3833	98.5862	151.8469
18	98.3789	97.4287	98.4134	224.2283	98.7605	97.6134	78.2309	98.5658	200.8699	98.8245	152.2156
19	98.5859	97.6357	98.6204	224.7002	98.9675	97.8204	78.3955	98.7728	201.2926	99.0315	152.5359
20	99.1016	98.1513	99.1360	225.8754	99.4831	98.3360	78.8056	99.2884	202.3454	99.5471	153.3337
21	99.4141	98.4638	99.4485	226.5877	99.7956	98.6485	79.0541	99.6009	202.9834	99.8596	153.8172
22	99.6602	98.7099	99.6946	227.1486	100.0417	98.8946	79.2497	99.8470	203.4859	100.1057	154.1980
23	99.8984	98.9482	99.9329	227.6917	100.2800	99.1329	79.4392	100.0853	203.9724	100.3440	154.5667

Figure 12: Partial list of inputs

As in Figure 13 i.e. list of inputs <512*60 double> are the features of the images that we are taken to train our neural network. These features are of open, drowsy and close eyes. 512 is size of our image and 60 are input images i.e. 20 of open eyes, 20 of drowsy eyes and 20 of close eyes.



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2	1	0	0
3	1	0	0
4	1	0	0
5	1	0	0
6	1	0	0
7	1	0	0
8	1	0	0
9	1	0	0
10	1	0	0
11	1	0	0
12	1	0	0
13	1	0	0
14	1	0	0
15	1	0	0
16	1	0	0
17	1	0	0
18	1	0	0
19	1	0	0
20	1	0	0

	1	2	3
1	0	1	0
2	0	1	0
3	0	1	0
4	0	1	0
5	0	1	0
6	0	1	0
7	0	1	0
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16	0	1	0
17	0	1	0
18	0	1	0
19	0	1	0
20	0	1	0

	1	2	3
1	0	0	1
2	0	0	1
3	0	0	1
4	0	0	1
5	0	0	1
6	0	0	1
7	0	0	1
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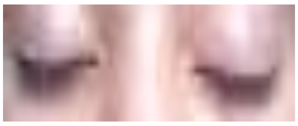
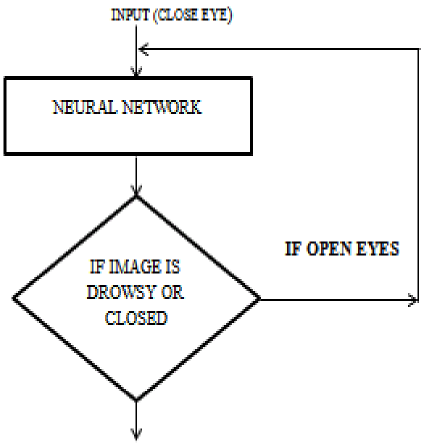
13	0	0	1
14	0	0	1
15	0	0	1
16	0	0	1
17	0	0	1
18	0	0	1
19	0	0	1
20	0	0	1

Fig.13Target pattern of open, drowsy and close eyes

The above figure are the three target patterns for our proposed neural network. In our work the target vector is encoded using one hot encoding method. One-hot refers to a group of bits among which the legal combinations of values are only those with a single high (1) bit and all the others low (0). For example, the output of a decoder is usually a one-hot code. Table A. displays the arrhythmia classes and their corresponding target vectors in one hot encoded form. The last step (after training) is the Image recognition for alarming signal: The trained neural network easily predicted whether the eyes are open, close or drowsy. In this case if the input image as close eye of the driver. Our neural network recognize the image as shown below and automatically an alarming signal is generated that alerts the driver.

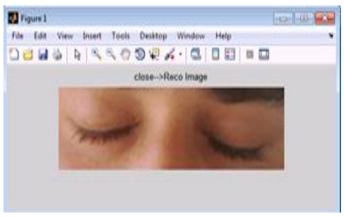
Input Image





Recognition image

Output Image



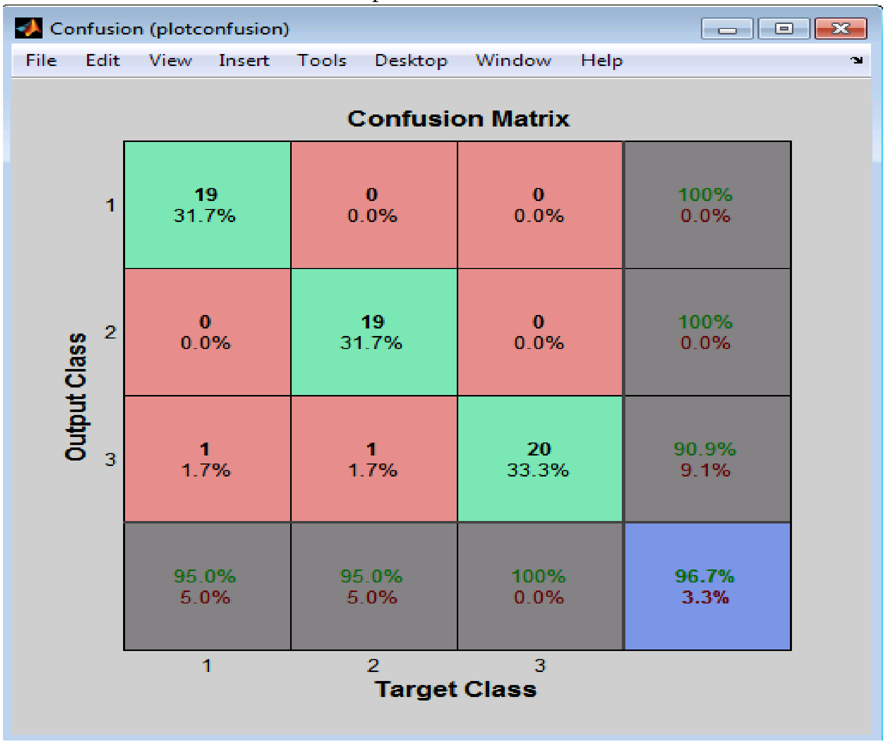
Our neural networks recognize the image as shown below: as close eyes and automatically an alarming signal is generated that alert the driver. The alarming signal is generated only in case of drowsy and close eyes. In our system open eyes represent activeness and close eyes represent sleepy and fatigueness of drivers.

III. RESULTS AND DISCUSSIONS

A. CONFUSION MATRIX

The performance of classifier is analyzed using confusion matrix which is also known as table of confusion. It displays the number of correct and incorrect predictions made by the model compared with the actual classifications in the test data. The confusion matrix lists the correct classification against the predicted classification for each class. The number of correct predictions for each class falls along the diagonal of the matrix. All other numbers are the number of errors for a particular type of misclassification error.

Table B**:** Overall performance confusion matrix



In Table B, we can see that when we consider overall data set than the accuracy reaches to 96.7% which is a very good amount. The rate of misclassification is less when compared to other phases. In this as we can see class1 is 0 times misclassified class 2 and class 3, class 2 was 0 times misclassified as class 1 and class 3 by 0.0%, class 3 was 1.7% misclassified as class 1 and class 2, and correctly classified as class 3.In Table we can see that the green boxes represent the final accuracy for each class as each class was correctly trained. Finally overall accuracy is shown in blue box which shows that each class classification was correctly learned by the arrhythmia classifier with zero mean square error and within stipulated parameters related to LM algorithm and gives 96.7 % results.

B. MEAN SQUARE ERROR

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function net.performFcn. Mean Squared Error is the average squared difference between outputs and targets. Lower values of (MSE) indicate better performance of the network and zero means no error.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

where, t –target ,
a - actual output
e – Error
N–Number of exemplars.

The performance graph is shown in Fig 14.

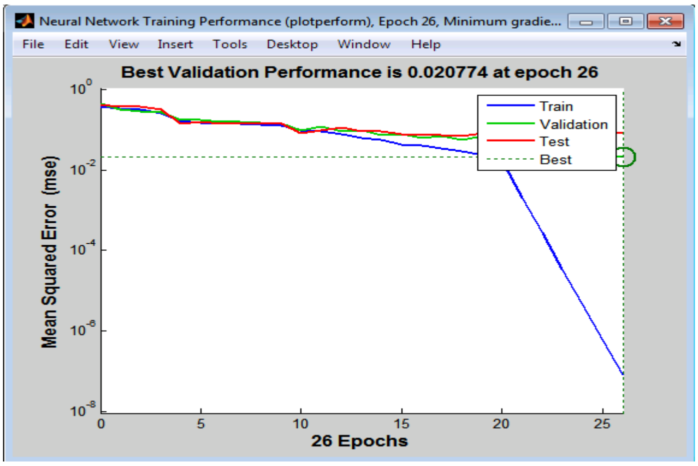


Fig.14: Performance Graph

The objective of Neural Network is to run simulation until it reaches minimum possible mean square error. From performance chart we can see that by simulating the conditions in each epoch we can see that there is not much variation in mean square error. It is more or less steady graph but as the epoch increases in each phase shown by red, green and blue lines the value reaches to best validation value of 0.02 which is very close to zero in ideal situation. This graph also shows that by just having 10 hidden layers of Neural Network we reached the point close to zero which shows that NN classifier was highly effective in knowing the nature of data set and knowing the causal association between different features like P peak, R peak, RR interval etc.

C. ERROR HISTOGRAM

Histograms are used to plot density of data, and often for density estimation: estimating the probability density function of the underlying variable. The total area of a histogram used for probability density is always normalized to 1. If the length of the intervals on the x-axis is all 1, then a histogram is identical to a relative frequency plot. There is no "best" number of bins, and different bin sizes can reveal different features of the data.

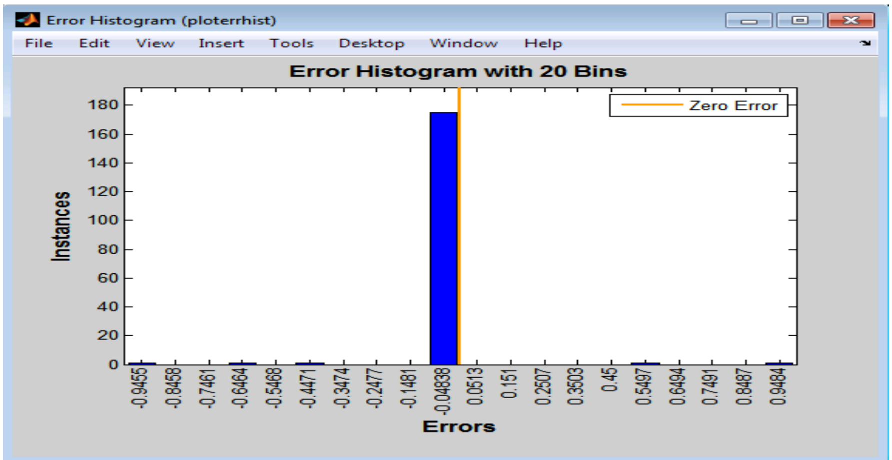


Fig.15 Error histogram

IV. CONCLUSION AND FUTURE SCOPE

A non-invasive system to localize the eyes and monitor fatigue is developed. Information about the degree of eye closure is obtained through various self-developed image processing algorithms. During the monitoring, the system is able to decide if the eyes are opened, drowsy or closed. When the eyes are drowsy or closed, a warning signal is issued. Neural network provides a completely different, unorthodox way to approach a control problem, this technology is not difficult to apply and the results are usually quite surprising and pleasing.

For future scope we suggest that that one can work on more features that can include the change is size and shape of iris when the person is drunk or when there is glossy appearance to eyes or must work on the concept of Horizontal Gaze Nystagmus for better accuracy using other machine algorithm like SVM.

A NOVEL METHOD FOR DETECTING DROWSINESS IN REAL TIME

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