Detection of Fatigue of Vehicular Driver using Skin Conductance and Oximetry Pulse: A Neural Network Approach

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ABSTRACT
Vehicular accidents are increasingly contributing towards loss of lives across the world. Timely detection of physiological and psychological parameters of the vehicular driver, which could cause various levels of physical and mental fatigue that lead to slower reflexes is therefore extremely important. As part of an ambitious research initiative, India is developing a pervasive computing solution for eliminating / reducing such accidents. As one of the component of such solution, a wearable computing system has been envisioned to be worn by the driver. A complex set of noninvasive and nonintrusive sensor-compute element integrated with appropriate e-textile would form the primary part of this wearable computer.

Out of the initial set of physiological parameters such as Skin Conductance, Oximetry Pulse, Respiration, SPO2, the current work focuses on the first two parameters to detect and monitor the mental fatigue / drowsiness of a driver. Using Neural Network approach, Multilayer Perceptron Neural Networks (*MLP NN*) have been designed to classify Pre and Posting driving fatigue levels. The performance of single hidden layer and two hidden layers based MLP NN have been discussed using the performance measures such as, Percentage Classification Accuracy (*PCLA*), Mean Square Error (*MSE*), Normalized Mean Square Error (*NMSE*), Area under Receiver Operating Characteristic Curve (*AROC*), Area under Convex Hull of ROC (*AHROC*). It was discovered that the performance of one hidden layer based MLP NN is comparable to the two hidden layers based MLP NN and there is slight rise in PCLA from One hidden layer to two hidden layer.

Keywords
Fatigue detection, Drowsy driver, Stress level, Skin Conductance, Oximetry Pulse, Multilayer Perceptron Neural Networks, Wearable Computer

1. INTRODUCTION
The fatigue is a complex phenomenon, indicating decrement in the performance of certain activity. It is not only associated with physiology, cognition and emotion but also correlates the other states such as boredom or drowsiness. Mainly there are two types of fatigue, physical and mental fatigue.

Physical fatigue affects the physical task performance, however the mental fatigue affects alertness involving task. Alertness of a driver while driving a vehicle is an important parameter to be monitored and maintained in order to avoid the vehicular accidents. Drowsiness / Mental fatigue gives a negative impact on slowing reaction time, decreasing situational awareness, impairing judgments [17], which focuses on required parameters of driving mechanism. The work presented here is a major subset of the BITS Life-Guard wearable computing research initiative. The overall project falls into wearable computing and mobile computing categories and thus is expected to be deployed within a pervasive / ubiquitous computing environment. This is because the wearable computer in form of a jacket shall have to be worn by the driver of the vehicle and this jacket would have, computing, sensing and communicating elements embedded in it. The communication involved would make use of body area network within wearable computing system of the jacket comprising of appropriate e-textile elements. If the computer determines that driver's reflexes are approaching the threshold level indicating driver's imminent inability to drive safely, it is expected to send a vibratory / audio alert. In event of a driver's (read wearer's) failure to respond in time to the alarm generated by the wearable jacket, the system in the jacket shall use Bluetooth-based wireless communication to the vehicular computer which with the help of the pre-fed GIS data and the location coordinates received from car's GPS receiver would help the vehicle to take over the control from the driver and safely park it while communicating with the surrounding intelligent transportation system infrastructure wirelessly.

The described work aims to design and implement a major element of this wearable computing system that aims to monitor the fatigue / drowsiness / stress level of a driver using physiological parameters such as skin conductance, pulse oximetry so that a simplified system can be built without distracting the driver and unaffecting his comfort level [4]. The paper presents the usage of physiological parameters of the body such as skin conductance and the oximetry pulse for classifying the pre and post driving fatigue state of the vehicular drivers.

An overview of existing systems
Various systems have been developed for the detection and monitoring alertness / drowsiness / stress level of the vehicular drivers based on visual approach, driver and vehicle behavioral approach and the physiological parameters such as Electroencephalograph (*EEG)*, Electrocardiograph (*ECG*), Electromyograph (*EMG*) and Electro-oculograph (*EOG*). The visual approach includes the image processing technique by taking the video images of the driver face periodically and

measuring eyelid closure [8], eye gaze, yawning frequency with the help of infrared cameras installed in the vehicle. Driver and vehicle behavior includes the drive movements, head nodding, snoring, yawning, steering wheel movement, vehicle lane departure, changes in vehicle speed etc. The systems using physiological parameters like EEG, EMG, ECG and EOG have performed very well for the detection of drowsiness of a driver, but these systems are distracting to the driver.

2. DATA COLLECTION-PROCESSING

2.1 Data Collection

The physiological body parameters of the drivers of varying age group of 20-55, driving a taxi car, lorry or truck, luxury bus, state transport bus were recorded for two different states of driver defined as pre driving and post driving, by using Nexus-10, Mind Media Schepersweg, The Netherlands. It is a 10-channel physiological monitoring and biofeedback platform that utilizes Bluetooth 1.1 class 2 wireless communication and flash memory technologies. The body parameters such as skin conductance, oximetry pulse, respiration, respiration rate and SPO2 were recorded for 3-5 minutes when a driver is fresh before going on drive after completing the drive of about 300-600 kms. The signals recorded were processed through Bio-trace+ software and the parameters were separated.

2.2 Skin Conductance

Skin Conductance / Galvanic Skin Response (*GSR*) is a measurement of electrical conductance between two points on the skin and is used in scientific research of emotional arousal. GSR measurement is also becoming commonplace in hypnotherapy and psychotherapy practice where it can be used as a method of detecting depth of hypnotic trance prior to suggestion therapy commencing. When traumatic material is experienced by the client, immediate changes in galvanic skin response can indicate that the client is experiencing emotional arousal. It is also used in behavior therapy to measure physiological reactions such as fear. Skin conductance is also a factor in some modern electronics to measure the activation of touch screen devices. GSR has been used to distinguish emotion states between anger and fear, conflict and no conflict, and stress level. The different set of features were extracted from recorded signals after dividing the signals into one frame, three frames and five frames and the scatter plots were observed for pre and post driving states. Later on the signals were divided into two second frames and a set of 18 features could be extracted.

2.3 Oximetry pulse

Oximetry pulse measures the oxygen saturation of blood and the changes in blood volume in the skin, producing a photoplethysmograph. The fatigue is also contributed due to reduction in supply of oxygen to the driver while driving. The driving performance is found to improve if the oxygen concentrations supplied is changed during the drive time of the driver [7]. It was shown that while driving a car, if the oxygen rate is lowered, fatigue is felt severely and that in the case of supplying a high-rate of oxygen, the feeling of fatigue is lowered to some extent and the reaction time is shortened.

2.4 Feature Extraction and Data Partitioning

Fatigue being complex phenomenon, it is essential to correlate it with as many physiological parameters as possible so that the decision of fatigueness and level of the fatigue can be determined. The skin conductance and the oximetry pulse signals were divided into two second frames for 10 selected subjects for pre and post driving states and 18 features were extracted using MATLAB. The features extracted Mean of Signal (*MOS*), Standard Deviation of Signal (*STDEVS*), Frame Energy (*FE*), Maximum Frequency (*MAXF*), Standard Deviation of Frequency Spectrum (*STDFS*), Mean of Frequency Spectrum (*MOFS*), their gradient in *two seconds and the slope*. The gradients of *MOS, SDOS, FE, MFREQ, SDOFS* and *MOFS* were computed for their values in consecutive two second frames. To illustrate the process of obtaining the gradients, let *MOS* computed over two second frames be **a1, a2, a3... an** for **n** number of frames corresponding to the signal. Then, the gradients over the frames were defined as **Δa1, Δa2, Δa3... Δan** such that **Δa1 = (a1-a2)/a1, Δa2 = (a2-a3)/a2 and so on ... Δ a(n-1) = (a(n-1)-an)/a(n-1)** are the indicator of relative change in the feature in the frame with reference to its initial value. In addition to this, the slopes of the above features were obtained, which indicates the rate of change of feature values. The slope is determined using **Sa12 = (a2-a1)/(t2-t1), sa23 = (a3-a2)/(t3-t2)**, ... where **Sa12** represents the slope of *MOS* for its values for frame 1 and 2 (a1 and a2) and t1 is the initial time of frame 1 and t2 is the final time of frame 1, similarly t2 is the initial time of frame 2 and t3 is the final time of frame 2, and so on. As the duration of each frame is 2 seconds, **t2-t1=t3-t2=...= 2 seconds**.

The features so extracted from skin conductance and oximetry pulse signals were combined together to give **2162 x 18** feature matrix. This feature matrix was then divided in the ratio **50:25:25** percent. First 50 % data has been used as training dataset used for training the neural network, next 25 % as cross validation dataset and the remaining 25 % has been used as testing dataset. Table 1 shows the data partitioning scheme and the details of dataset 1 and 2, which would be referred ahead.

The input matrix of 2162x18 was initially given as input to various neural network models such as Multilayer perceptron (MLP), Generalized Feed forward (*GFF*), Jordon Elman (*JE*), Modular Neural Network (*MOD*), Radial Basis Function (*RBF*), Self Organized Feature Map (*SOFM*), Principal Component Analysis (*PCA*), Time Lag Neural Network (*TLR*), Recurrent Neural Network (*RN*) and Support Vector Machine (*SVM*) models available in Neuro-solutions-5.1. All the networks were trained with three runs for 5000 epochs for one hidden layer and two hidden layer. The basis used was minimum MSE for finding the number of hidden layer Processing Elements (*PE*). The comparative performance of the two hidden layer neural networks for PCLA and MSE were plotted. It is observed that the average PCLA for test dataset is maximum as 90.57 % for MLP NN with minimum MSE as 0.068 as compared to all other neural network models. Hence the design of MLP NN for one hidden layer and two hidden layer has been carried out and presented in further part of the paper.

Table 1. Data Partitioning Scheme

Data Partition	Training instances	Cross validation instances	Testing instances
Set 1 (Normal tagging)	1:1082 (1082 samples)	1083:1622 (540 samples)	1623:2162 (540 samples)
Set 2 (Reverse tagging)	1:1082 (1082 samples)	1083:1622 (540 samples)	1623:2162 (540 samples)

3. DESIGN OF MLP NN

The MLP NN for approximation of the mapping from input to the output of the system provides simplicity and the fact that it is well suited for online implementation [10]. The design of MLP NN is based on *Processing Elements*, which compute a non-linear function of the scalar product of the input vector and a weight vector. The neural network design mainly consists of defining the *topology* (i.e., the arrangement of PEs, connections, and patterns into the neural network) and the *architecture* (i.e., the selection of the number of PEs for each layer necessary for the specific application of the topology) of the network. In MLP neural networks, the PEs in a layer are connected to all the neurons in the following layer through unidirectional links represented by connection weights. The MLP requires the determination of the activation functions and the thresholds of the PEs, as well as of the connection weights. First, the activation functions and the thresholds are defined by a recursive optimization procedure. Then, the connection weights are computed by means of a learning algorithm such as back-propagation.

Supervised training of a MLP is viewed as a problem in numerical optimization. The error surface of a MLP with supervised learning is a highly nonlinear function of the synaptic weight vector. When a NN has been trained, the next step is to evaluate it. This is done by a standard method in statistics called *independent validation*. This method divides the available data into a training set and a test set. The entire data set is usually randomized first. The training data are next split into two partitions; the first partition is used to update the weights in the network, and the second partition is used to assess (or cross-validate) the training performance. Since it is very likely that one ends up in a "bad" local minimum, the network should be trained a couple of times (typically at least three times), starting from different initial weights. The test data are then used to assess how well the network has generalized. The learning and generalization ability of the estimated NN based classifier is assessed on the basis of certain performance measures such as *MSE, NMSE, PCLA* and *ROC* parameters such as *AROC, AHROC*. Nevertheless, for classifiers the percentage of correct classification is the most crucial parameter. The network parameters and their range of variation used, corresponds to Number of Hidden Layer (1-3), Hidden layer PEs (2-100), Learning Rate Parameter (0-1), Momentum Constant (0-1), Transfer Functions (Tanh, LinTanh, Sigmoidal, LinSig, Bias Axon, Linear Axon, SoftmaxAxon, Axon), Learning algorithms (Momentum, Conjugate Gradient, Levenberg Marquardt, Quickprop, Delta-Bar-Delta, Step) and number of epochs (0-5000).

3.1 One hidden layer based MLP NN

A single hidden layer MLP NN with hyperbolic Tanh T*ransfer Function* (TF) Tanh and *Momentum* (MOM) LR for hidden layer and output layer was trained three times for the input feature matrix as per Table.1 by varying hidden layer PEs from 2 to 100 in step of 1 and the network was tested for classification accuracy on test dataset, *Cross Validation dataset* (CV dataset) and Training dataset corresponding to each value of hidden layer PE. Total number of training epochs allowed was 5000. The PCLA and MSE were recorded for each PE value. Plots of PCLA over test, CV and training datasets and MSE were plotted and it was found that the average PCLA over test dataset comes out to be 92.61 % at 28 PEs at hidden layer and the MSE is also one of the minimum values as 0.064962. The MLP NN with 28 hidden PEs with Tanh Transfer function was further trained three times on the same dataset and the *Learning Rules* (LR) were changed. MSE versus Epochs for different LR and indicates that the network converges very fast with momentum LR. Further the network with momentum LR, the transfer functions were changed and it is found that average PCLA over test dataset reaches its *maximu value* for Tanh TF and MOM LR. The network parameters Learning Rate and Momentum Constants were also varied from 0.001 to 1 in step of 0.1 for output layer and the optimal performing set of one hidden MLP is shown in Table 2. The final network was further trained and tested for dataset 2 (using Reverse Tagging) and it was found that the values of PCLA and MSE reached 89.27 % and 0.08356978 respectively. For a classifier's best performance, AROC is supposed to be unity, ideally. The AROC values obtained for test dataset 1 and test dataset 2 were 0.966244 and 0.949509 respectively. Table 4 shows the test results of one hidden layer based MLP NN for the two datasets.

Table 2. Optimal Parameters of One hidden layer based MLP NN

Parameter	Hidden Layer	Output Layer
Processing Elements	28	2
Transfer Function	TANH	TANH
Learning rule	Momentum	Momentum
Learning Rate	1.0	0.7
Momentum Constant	0.1	0.9

3.2 Two hidden layers based MLP NN

Two hidden layers based MLP NN was designed by following same procedure. Hidden layer 1 and hidden layer 2 PEs were varied from 2-100 each and the network was tested over test, CV and training datasets after training three times. Initially, Tanh TF and MOM LR were used and the maximum PCLA over test dataset obtained was 93.17 % at MSE as 0.058051 for L1 PE 65 and L2 PE 80. Further the LR and TF were varied for optimization of the performance of neural network and it was found that Tanh TF and MOM LR is performing optimally. Figure.1 shows that PCLA reaches its *maximum* value at L1 PE 65 and L2 PE 80 and Figure.2 shows variation of MSE with the variation of L1 and L2 PEs. Figure.3 illustrates performance comparison of Learning Rules and it is clear that the network converges faster for momentum LR. Table.3 depicts optimal parameters of two hidden layers based MLP NN. This MLP NN with Tanh TF and MOM LR, hidden PEs at L1 as 65, hidden PEs at L2 as 80, was further trained and tested by varying learning rate and momentum constant at output layer from 0.001 to 1 in step of 0.1 and it was found that it gives optimal performance at 0.001 learning and 0.7 momentum constant at output layer. Thereafter this network with optimal parameters was tested for dataset 1 (Normal Tagging) and dataset 2 (Reverse Tagging) and the performance measures of the MLP NNs, thus obtained, have been compared in Table 4. The ROC tables giving the details of instances of correct detection and incorrect detection (false positives) were recorded as the bias at the output layer was varied from -1 to +. As a result of this process of testing the network with testing and training data partitions of the two datasets and the ROC curves were plotted as shown in Figure 4 and Figure 5. The specificity (false detection rate) was calculated for 95 % correct detections as presented in Table 5 along with the corresponding values of PCLA. Table 5 provides comparatives results of on hidden layer and two hidden layers based MLP NNs.

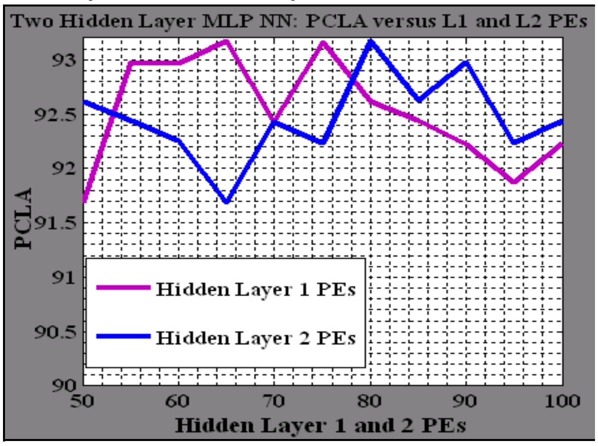

Figure 1. Two hidden layers based MLP NN: Showing that PCLA is maximum of 93.17 % at L1 PE 65 and L2 PE 80

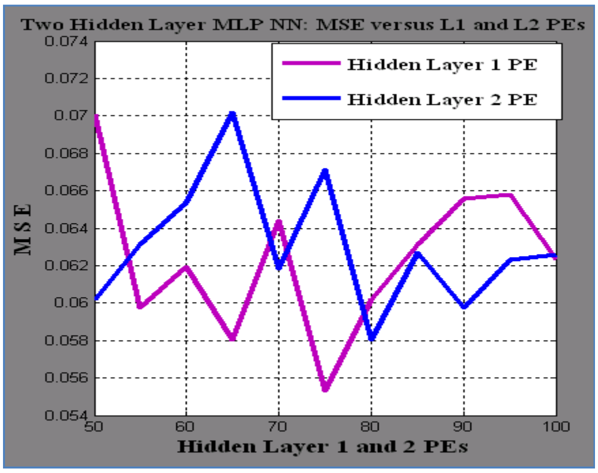

Figure 2. Two hidden layers based MLP NN: Showing MSE for L1 PE and L2 PE

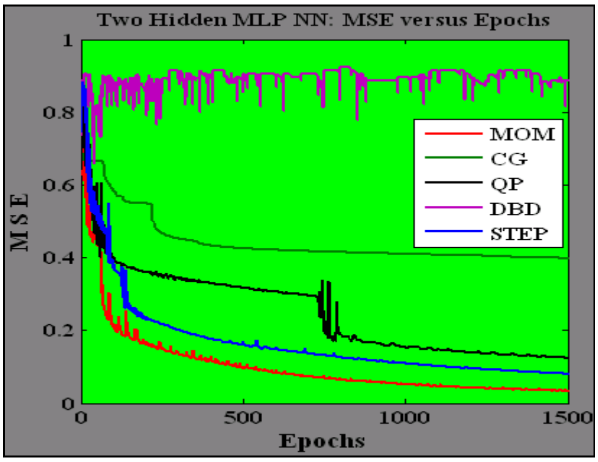

Figure 3. Two hidden layer MLP NN: Comparison of LR

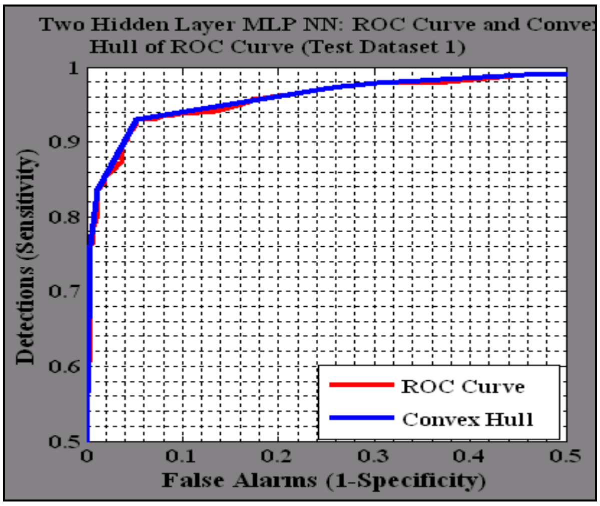

Figure.4 ROC curves for Two hidden layer MLP NN Set 1

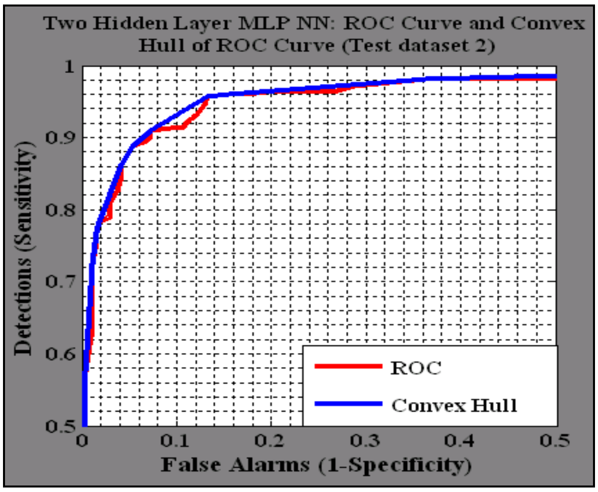

Figure 5. ROC curves for Two hidden layer MLP NN Set 2

Table.3 Optimal Parameters of Two hidden layer MLP NN

Parameter	**Hidden Layer-1**	**Hidden Layer-2**	**Output Layer**
Processing Elements	65	80	2
Transfer Function	TANH	TANH	TANH
Learning rule	Momentum	Momentum	Momentum
Learning Rate	1.0	0.1	0.001
Momentum	0.7	0.7	0.7

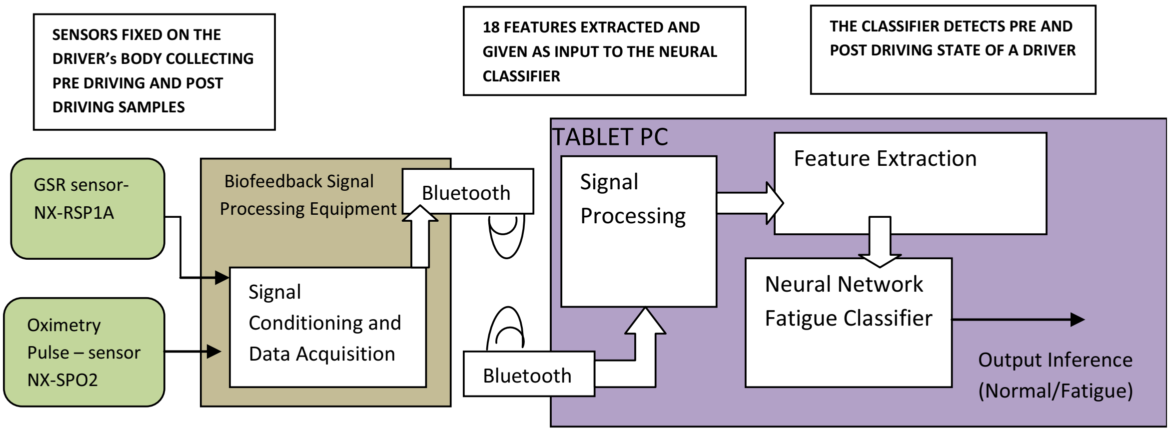

Figure 6. Architectural Representation of the Fatigue Detection System

Table.4 Performance Measures of One Hidden and Two hidden layers based MLP NN

Performance Measures	**Set 1: Forward Tagging**		**Set 2 : Reverse Tagging**	
	One Hidden MLP NN Average	Two Hidden MLP NN Average	One Hidden MLP NN Average	Two Hidden MLP NN Average
MSE	0.06496156	0.05805105	0.08356978	0.06565077
NMSE	0.25987832	0.23223288	0.33444427	0.26273282
PCLA	92.6122567	93.1740544	89.2786561	91.4937418
AROC	0.966244	0.97451	0.949509	0.965285
AHROC	0.968089	0.975909	0.952603	0.968654

Table.5 ROC Parameters for One Hidden and Two hidden layers based MLP NN

Data set	**Area under an ROC curve**		**Area under convex hull of an ROC curve**		**Specificity**		**Average PCLA**	
	One Hidden MLP NN	Two Hidden MLP NN	One Hidden MLP NN	Two Hidden MLP NN	One Hidden MLP NN at 95 % Correct detections	Two Hidden MLP NN at 95 % Correct detections	One Hidden MLP NN %	Two Hidden MLP NN %
Testing (Set1)	0.9662	0.9745	0.9680	0.9759	80 %	85 %	92.6122	93.1740
Training(Set1)	0.9897	0.9976	0.9909	0.9982	98 %	99.96	97.493	98.5372
Testing (Set2)	0.9495	0.9652	0.9526	0.9686	87 %	87 %	89.2786	91.4937
Training(Set2)	0.9853	0.9945	0.9863	0.9950	92.5	99.85 %	95.0819	96.2729

3.3 Architectural Representation of the system

At this stage, it may help to be able to visualize the entire setup through the architectural representation of the fatigue detection system as shown in Figure 6. This diagram is largely self explanatory. Skin Conductance (SC) and Oximetry Pulse (OP) sensors shown in the diagram were worn by the driver and resultant recording of the signals was carried out by using a Biofeedback signal processing equipment for the pre and post driving states. Signals from the equipment were transmitted wirelessly using Bluetooth and were received in the Tablet PC for further processing. After signal processing, eighteen features were identified, as discussed earlier. Subsequently, the corresponding data were separately fed to one hidden layer MLP NN classifier and two hidden layer MLP NN classifier for verifiable detection of the fatigued or normal state of the driver.

4. CONCLUSION

The presented work has been carried out primarily as a part of the doctoral research of the first author and its final aim is to assist in design and implementation of a wearable computing system for the driver to prevent road accidents. The attempt to correlate Fatigue level of a driver with Skin Conductance and

Oximetry Pulse as physiological parameters has resulted in a non-invasive technique for the detection of fatigue level. Figure 6 illustrates the architecture of the fatigue detection system.

Signal processing technique has been applied in the form of feature extraction prior to the implementation of the Neural Network that has successfully reduced the computational resources. As a classifier, the best two hidden layered MLP NN(18-65-80-2), with TANH transfer functions in the hidden and output layer, is seen to perform efficiently. MLP NN being fastest Neural Network, ideally suitable for real time applications proves to classify the fatigue level of any person in general and the driver in particular. Thorough analysis of single hidden layer MLP NN and two hidden layers based MLP NN confirms that the two hidden layers based MLP NN with TANH transfer function and Momentum Learning Algorithm gives maximum classification performance with an average accuracy as 93.17 %. The classification accuracy is maintained also for the reverse tagging order of the exemplars. The momentum algorithm was found to converge well as compared to other learning algorithms. Further it is observed that single hidden layer MLP NN (18-28-2) with TANH and MOM has performed well near the performance of two hidden MLP NN (18-65-80-2) giving, PCLA over test dataset as 92.6 %. The ROC analysis of both the Neural Networks designed states that both the networks are consistently good, giving area under ROC above 0.95 and nearly equal to unity. The variation of Learning Rate and Momentum Constant at output layer has improved the performance of the networks.

Although, fatigue is a complex phenomena *Skin Conductance* and *Oximetry Pulse* can be used as few of the identifying physiological parameters and it is expected that fusion of other non-invasive physiological parameters, such as, Respiration, Respiration Rate and SPO2 shall lead to improvement in the classification accuracy of fatigue level of a driver, with additional robustness in the detection system.

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