Fall Pattern Classification from Brain Signals using Machine Learning Models

Janet Light , Kalaiselvi T, Xiaoyi Li, Abhishek Raghu Malali

Abstract— **The aim of this study is to develop a model for a fall pattern detection from the EEG signals of elderly and Alzheimer's disease people. Initially, a 4-channel EEG device is used to observe in a noninvasive manner, the brain signals from the prefrontal lobe of the people in real-time. Then the signals are captured in a base station using wireless biosensors. In the base station, a rapid and fully automatic algorithm is implemented to extract the required features from the brain signals and classify them into normal and fall patterns. If it is classified as a fall then the system will warn the caretakers. The selection of features and methods for classification is crucial for the model for accurate detection. We have selected some common statistical features to model our system. The popular supervised machine learning techniques like SVM and ANN are used to classify the signals based on the selected features. With these base models, we have achieved 100 % detection and approximately 98% predictive accuracy.**

Index Terms: **Brain Signal Analysis, Fall Detection Model, Machine Learning Techniques, Use of Wireless Biosensors.**

I. INTRODUCTION

Fall among the elderly causes serious injury, often leading to impaired mobility which further complicates their healing and recovery process [1]. The finding in [2] shows that almost 61 percent (8 out of 13) of the patients, who are with recurrent episodes of nocturnal fall have had fall during sleep. Fall detection for the elderly population has been an active research topic in the past decade, due to increased demand for accurate solutions and potential market for the healthcare industry. What we have developed is a monitoring system that prevents fall incidents during sleep, which is nothing but an accurate fall detection and prediction system.

Depending on the type of device and how it is used, the methods of fall detection can be classified into using any one of the following three groups of devices: Ambience devices, Camera devices and Wearable devices. This study focuses on the use of wearable devices. In our earlier work, we have used posture and motion devices for fall detection [1]. Though we obtained high accuracy in fall detection during daily activities, the detection and prediction attempts were not efficient during sleep. The objective here is to develop an EEG signal based sleep monitoring and warning system. The system captures and analyzes sleep EEG signals in real-time for fall patterns. In addition to detecting different types of fall patterns, the real-time EEG data is compared to preceding emergency event patterns to predict anomalous incidents (such as fall) quickly and accurately.

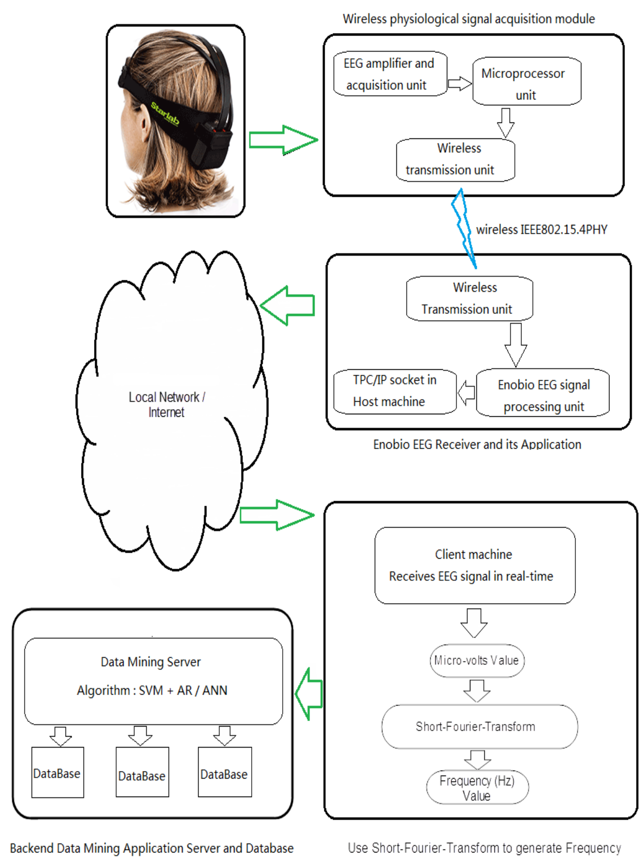

Figure 1: System components

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J.Light is Professor at University of New Brunswick, Saint John, New Brunswick, E2L4L5, Canada (corresponding author phone: 506-648-5621; e-mail: jlight@unbsj.ca).
T. Kalaiselvi, is Faculty at Gandhigram Rural Institute (Deemed University), India. (e-mail: kalaivpd@gmail.com).
X. Li is a Graduate student with the University of New Brunswick, Saint John, NB, Canada (email: sli@cgsinc.ca)
A.R. Malali is a EEE student at NIT, Karnataka, India (email:abhishekmalali@gmail.com)

The data collection system consists of a 4-channel biosensor device (Enobio®) and its wireless signal acquisition module**,** Matlab TCP interface application and machine learning algorithms. The Enobio® devices includes a light-weight head gear with four biosensor nodes connected to a wireless transmitter tied to the head gear. A USB receiver connected to a computer receives and process EEG data. The software reads, writes, and plots the EEG the signals as shown in Fig.1. The micro-volt data signals can also be exported to other servers in real time. This EEG data is in the .edf (European data format) format and is subsequently read by MATLAB on which the data mining system is running.

Machine learning techniques are generally helpful in feature extraction among EEG signals, since the recorded signals usually tend to have variable bias and uncertain changes, which make the feature classification difficult. So, thresholding for sleep-EEG fall detection is not a feasible approach. In, most cases the EEG values vary from person to person and are not constant even for different recordings for the same person. The sensed voltage values can vary up to several thousand micro-volts for different people. Hence statistically derived thresholds might not be a robust mechanism to detect a fall. Artificial neural networks (ANN) and support vector machine (SVM) have been used as a form of supervised learning models (SLM) in detecting certain features in the captured EEG data in [4] and many other systems.

With advanced pattern recognition techniques coupled with machine learning techniques, fall pattern classification is carried out in this study. The system is designed to preprocess the data into a specific feature set which is provided to the SLM as an input. The SLM has been trained on a training set which is already compiled using many sets of fall data. A co-validation set is used so as to test the trained hypothesis. A trade-off should be carried out between the training and co-validation set so as to maintain maximum co-validation accuracy. The hypothesis is then checked and validated on a test set.

The paper is arranged as follows: Section II describes the proposed system framework and the models used; Section III presents details of datasets collection; Section IV discusses the results and the conclusion is given in section V.

II. METHOD

The software framework of the proposed system is given in Fig.2. At first, the EEG signal is received as micro-volts data through the Enobio® System and sent wirelessly to a server which hosts a real time EEG data classification application. The raw signals are preprocessed to remove any artifacts and segmented for analysis. Then from the preprocessed and segmented signal portion, the feature extraction and selection process is executed to select the features corresponding to EEG-Normal and EEG-Fall activities and then fed into the classification process.

Here two forms of SLM are used to classify and verity the accuracy. They are SVM and ANN. The prediction frameworks used by these models are explained in the following sections. Based on the results and interpretations given by these models, if fall pattern is identified, a warning signal will be sent to the caretaker.

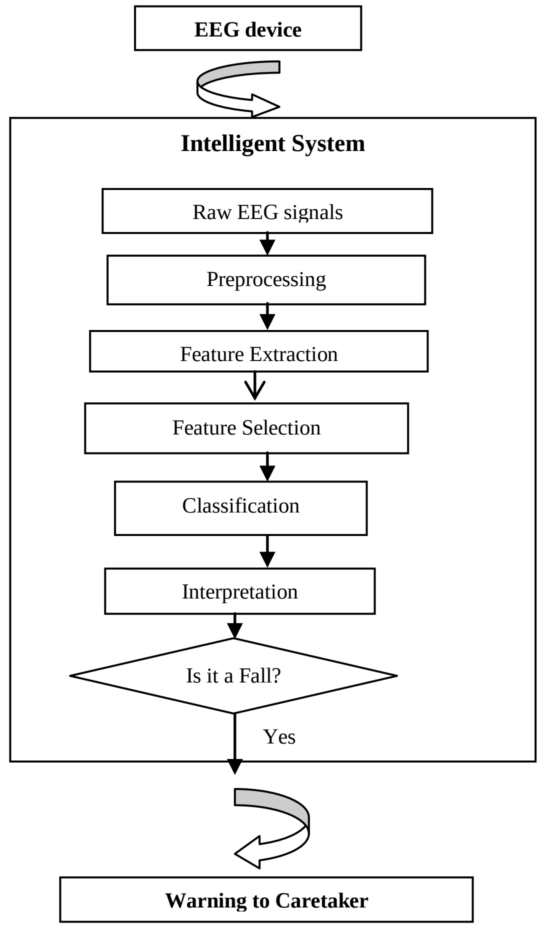

Figure 2: Proposed System Architecture

A. SVM Model

The SVM proposed by Vapnik [5] has been used widely in data classification. The model architecture is given in Fig.3. Initially the raw EEG data will be pre-processed by calculating the differences of data received from the multi-channels. Because micro-volt data is generated from each channel by the Enobio**®** System, every 4 millisecond, the system calculates a mean value from every 125 micro-volt data, which is the data from half second signal. The time boundary may be changed if necessary. The system then generates the differences of micro volt between every mean value. In addition, the Short Time Fourier Transform (STFT) can be used to generate frequency (Hz) value from raw micro-volt data during a time domain (left as future work).

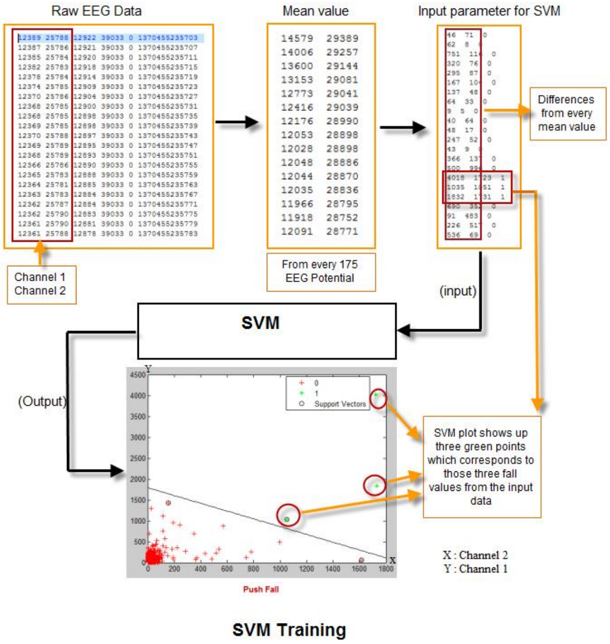

Figure 3: SVM model

Finally, the SVM is used to train and classify the input values which are those micro-volt differences generated from the last step.

The SVM tool used from Matlab requires three groups of parameters as input. The first and the second group are value inputs from the final steps. These values are from EEG raw data at Channel 1 and Channel 2. The third group is either 0 or 1 which is generated based on the value of differences. The third group is used to inform the SVM of which value/values belong(s) to 0 or 1, and this group is only used for training SVM as given in Fig.3. After necessary training is completed, the SVM will be able to detect any incoming values from the first two groups, and the third group will not be used anymore.

The method to determine the value 0 or 1 for the third group is crucial. Based on our previous sleep monitoring study [6], any movement during sleep causes certain brain potential which can reach to 1000 uV difference between every half second during that motion. In addition, a fall during sleep can make this difference potential appearing every channel. Therefore we then find if both channels (Channel1 and Channel 2) are receiving difference potential higher than 1000uV, and then give 1 to this pair of values in difference potential, and give 0 to any other cases. Once the parameters are received by the SVM, it will be trained to recognize which pair/pairs of the difference potential can be treated as fall (1) or not fall (0).

B. *ANN Model*

The ANN framework used by our study is given in Fig.4. In the ANN model development, the principal component analysis (PCA) plays a major role in the feature selection from the multi-channel signals [7]. PCA is the most effective tool available to get fundamental components from the correlated channel data [8]. These fundamental components are a measure of difference in patterns between the time signals, which is significant since the EEG channel data tend to be dissimilar in case of a major event like a fall. So as to distinguish between minor events or major events, additional features in the form of normalized standard deviation and variance of all the three channels are used. The normalized standard deviation is seen to be high in fall periods. The data before being processed to find the features is passed through a high pass filter and the DC bias is removed so as to get more accurate and relevant features. Also the calibration data included in the fall data during which the dry electrodes are calibrated are filtered out so as to reduce chances of false positives. During the calibration period, the DC bias fluctuates rapidly, which might not be eliminated even with the help of filters. Combined together, we get the feature vector which is used to train the neural network.

Since Neural networks is a form of supervised machine learning, each data or feature vector has to be manually classified and checked, if a major event is occurring. The EEG-Fall (major event) is classified as 1 whereas the EEG-Normal is classified as 0. The data included in the study consists of both involuntary as well as voluntary EEG-Fall. PCA is used as an Eigen vector-based multivariate analysis. PCA is used in a dimension reduction technique and is used to get a smaller picture with large channel data. It moves much of the variance into the first few components. The weights obtained in the PCA carried out with the EEG data are neglected for our purpose.

The neural network models on which the testing and classification are carried out are three and four layer respectively. The neural networks use sigmoid functions to calculate the cost. The gradients are calculated to be fed to an iterative constrained continuous differentiable multivariate function solver, which adjusts the weights so as to get the least cost. The weights are calculated using the back-propagation algorithm.

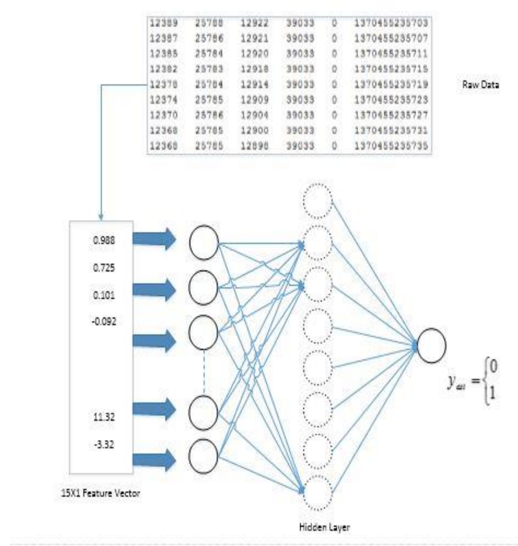

Figure 4: ANN model

III. Data Collection

The initial obstacle to designing an AI decision system is the data collection procedure. Despite continuous monitoring for collecting credible fall data from normal elderly and Alzheimer's disease patients [6], the team failed to collect any significant data, since only one fall occurred over the entire duration during which the data acquisition gear was used and it happened when the gear was not on the corresponding patient. To solve this issue, the data was synthesized with normal human subjects.

The inner ear contains the cochlea and two other organs which are responsible for sensing human balance. The first organ detects the position of the head, whereas the second organ detects the degree of rotation of the head. Together these two organs are very well capable of detecting a fall. In case of Alzheimer's disease patients, even though the signals from these balance organs are interpreted by the temporal lobe, the corrective action is not taken by the cerebellum. Hence the decision has been taken to position the EEG sensors on the temporal lobes. An extra sensor was placed in between the frontal lobes to check for any other brain response during the fall.

The fall data collection experiments involved the subject lying on a bed, being constrained to a very small portion. This increases the tendency of the subject to fall which is in most cases when the person is in sleep and unconscious movements can cause instability leading to a subsequent fall. Once the person has fallen asleep, the subject either falls himself or is given a small push, which results in the fall. This was carried out to monitor any change in the EEG output depending upon the type of fall. During a fall, the data collection is carried out for some time after the fall so as to see recovery statistics. Our theory about the brain's fall detection capability was confirmed when the temporal lobes showed the maximum and earliest change in the voltage signals during the beginning of the fall. Table 1 shows the age of the subject along with the fall type for each dataset recorded

Table 1: The details of dataset used for the experiment

No.	Age	Type of Fall
1	26	Voluntary
2	26	Pushed
3	20	Pushed
4	20	Pushed
5	20	Voluntary
6	20	Pushed
7	20	Pushed
8	20	Voluntary
9	20	Voluntary
10	20	Voluntary
11	20	Voluntary
12	20	Voluntary
13	20	Voluntary
14	20	Voluntary
15	20	Voluntary
16	20	Voluntary
17	20	Voluntary
18	20	Voluntary
19	20	Voluntary
20	20	Voluntary

IV. Results and Discussion

The test results of both SVM and ANN models are presented here. The test data sets consisted of 20 sleep-like fall EEG results (Pushed and Voluntary) to the single person for ANN model testing and sleep EEGs from 20 different people for SVM model testing. Seventeen of the ANN data-sets were used to train the SVM, and the remaining three for testing. The test showed 100% fall detection by the SVM model. The result of SVM test is given in Fig.5.

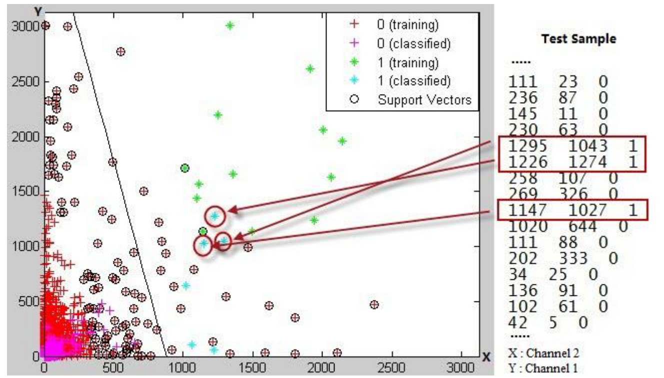

Figure 5: SVM Test

The blue star icons represent those fall signals which are identified by SVM and showing up on the right hand side of hyperplane. The pink plus icons represent those non-fall signals which is also identified by SVM and placed in the left hand side.

The results prove that SVM is able to classify 100% the fall incidents by proper training. However, it can only detect when it happened and was not be able to predict the incident before it happened. We are currently working on the frequency signal and try to combine both EEG potential and its frequency value, so that we may get more information from real-time EEG data before a fall.

In the ANN model, prediction and recall are used as a parameter in error analysis, in which the f-parameter being used decides the best trade-off between precision and recall. Recall should be kept low so as to prevent false positives which reduce the practicality of the system in different situations. The number of units in the hidden layer can be changed accordingly as given in Table 2, to see a difference in the results and is carried out until the best possible result is achieved. Usually 500-1000 iterations are used to get the least cost. A four-layer network is also similarly trained so as to improve the efficiency and get an idea about the dominating feature vectors.

Training uses around 1500 feature vector sets. Initial training was carried out with lesser sets and after a thorough error analysis the numbers of training sets were accordingly increased to achieve better accuracy. Co-validation set usually has 500 sets and the training set has 500 feature vector sets.

The number of output neurons is kept as one in this study but will eventually be increased with inclusion of more movements. Thresholding is used so as to ensure accurate classification since the output is usually decimal value in between 0 and 1. 0.4-0.6 is found to be a good threshold depending upon the co-validation set and the known properties of the sigmoid function. The accuracy achieved so far is approximately 98%.

Table 2: Test Set Accuracy by ANN model

Number of Units in Hidden Layer / Regularization Parameter	15	25	40
2	81.36	84.27	86.35
0.1	91.13	93.35	93.35
0.02	94.72	97.71	96.36
0.002	95.83	95.83	96

V. Conclusion

In this study, our main aim is to develop accurate prediction models for a fall system. In this paper, 100% fall detection using SVM model is proved. Further, feature extraction of brain signals taken for different types of fall like pushed and voluntary fall using ANN model is presented. Further the accuracy of the system is tested with both SVM and ANN models. Both SLM models used statistical based features of multi-channel EEG data to run their respective system.

Another choice of feature extraction based on Fourier transform or Wavelet transform may be able to improve the results obtained. In future, we plan to extract more features relevant to the nature of EEG signals and fall activity based on spectrogram, scalogram, power and energy based features, etc. Popular signal processing transformation techniques like Fourier or wavelet could be used to standardize our feature selection process. In addition, some of the unsupervised classification methods will be explored to quicken the prediction process.

References

[1] S. Abbate, M. Avvenuti, G. Cola, P. Corsini, J. V. Light, and A. Vecchio, 'Recognition of false alarms in fall detection systems', in the 1st IEEE International Workshop on Consumer eHealth Platforms, Services and Applications (CCNC'2011 Workshop CeHPSA), Las Vegas, NV, USA, 2011, pp. 538–543.

[2] David L. Jardine, "Fainting in your sleep?", C. T. Paul Krediet, Pietro Cortelli and Wouter Wieling Clinical Autonomic Research, vol.16, no.1, February, 2006.

[3] Xinguo Yu, "Approaches and principles of fall detection for elderly and patient", in the 10th IEEE International Conference on e-Health Networking, Applications and Services (HealthCom 2008), pp.42-47, 2008.

[4] B. H. Jansen and P. R. Desai, "K-Complex Detection using multi-layer recurrent neural networks perceptrons and recurrent networks" Int. J. Bio-Med. Comput., vol. 37, pp.249-257, 1994.

[5] V. Vapnik, "The nature of statistical learning theory", New York. Springer-Verlag, 1995.

[6] J. Light, S. Abbate, L. Xiaoyi, "Developing cognitive decline baseline for normal ageing from sleep-EEG monitoring using wireless neurosensor devices", in the 24th IEEE Electrical and Computer Engineering (CCECE), Canadian Conference, 2011, pp 001527 - 001531.

[7] Guyon and A. Elisseeff, "An Introduction to Variable and Feature Selection", Journal of Machine Learning Research, pp. 1157-1182, 2003.

[8] Abdulhamit Subasi and M.Ismail Gursoy, "EEG Signal classification using PCA, ICA, LDA and support vector machines", vol.37, pp. 8659-8666, 2010.

Janet Light received her Bachelor degree in Electronics and Communications Engineering in 1983, Masters in Electrical and Electronics Engineering in 1990 and PhD in Computer Science in 2002 from India. Her research interests are in wireless & mobile computing, ubiquitous computing, sensor networks, network traffic study and security. Some of her research projects are: 911 pre-hospital emergency service system, mobile middleware for eHealth, and health monitoring systems using wireless sensors. She is an IEEE member since 1998.

Kalaiselvi T received her MCA in 1997 from Avinashilingam University and her PhD in Computer Science from Gandhigram Rural University, India in 2010. Since then she is a faculty in the same university. Her research interest is in Medical imaging especially brain imaging and currently developing intelligent systems to recognize brain abnormalities from MRI Head scans.

Xiaoyi Li is a MCS student at UNB Saint John. His thesis is on Fall Prediction Model development using SVM. He has a Bachelor degree in Computer Science from UNB Saint John.

Abhishek Raghu Malali is a final year EEE student at National Institute of Technology, Suratkal, India. His research interest is in use of Artificial Neural Network modeling for signal analysis.