

Received October 20, 2020, accepted November 17, 2020, date of publication November 25, 2020, date of current version December 9, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3040437

HealthSOS: Real-Time Health Monitoring System for Stroke Prognostics

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This work was supported by the National Research Council of Science & Technology (NST) funded by the Ministry of Science, ICT and Future Planning (MSIP), Korea Government under Grant CRC-15-05-ETRI.

ABSTRACT Electroencephalography (EEG) is immediate and sensitive to cortical impairment resulting from ischemic stroke and is considered as the potential predictive tool of stroke onset, and post-stroke clinical management. Brainwave monitoring outside the heavily equipped clinical environment demands a low-cost, portable, and wearable EEG system. This study aims to assess the feasibility of using an ambulatory EEG system to classify the stroke patient group with neurological changes due to ischemic stroke and the control healthy adult group. HealthSOS, a real-time health monitoring system for stroke prognostics, is proposed here, which consists of an eye-mask embedded portable EEG device, data analytics, and medical ontology based health advisor service. This system was investigated with 37 stroke patients (mean age 71.6 years, 61% male) admitted in the emergency unit of a hospital and 36 healthy elderly volunteers (mean age 76 years, 28% male). EEG was recorded in resting-state using the portable device with frontal cortical electrodes (Fp1, Fp2) embedded in an eye-mask within 120 h after the onset of symptoms of ischemic stroke (confirmed clinically). The EEG data acquisition of the left and right brain hemispheres was done for at least 15 minutes in the awake resting state while subjects laid down on the bed. The statistical result shows that the revised brain symmetry index (rsBSI), the delta-alpha ratio, and the delta-theta ratio of the stroke group differ significantly from those of the healthy control group. In the machine learning analysis, the support vector machine (SVM) model shows the highest accuracy (Overall accuracy: 92%) and the highest Gini coefficient (95%) in classification performance. This study will be useful for early stroke prognostics and the management of post-stroke treatment.

INDEX TERMS Sensor systems and applications, brain-computer interfaces, neuroscience, biomedical monitoring.

I. INTRODUCTION

Stroke is one of the leading neurological disorders in adulthood and it is the second leading cause of death and disability in the world among the elderly population [1]. Early detection of stroke onset is life-saving [2]. Stroke identification and detection of stroke severity affect mortality rate, rehabilitation, medical cost, and quality of post-stroke life. In many cases, stroke symptoms are not visible at the early level of ischemic events. So, the decision of referral to a clinical diagnostic center and detail neural and pathological assessment may be delayed [3]. Late identification of ischemic stroke may lead to cognitive impairment and the economic burden

of stroke care with a mental impairment is three times greater than those without cognitive damage [4].

Tracking the behavior of the neuro-electrical system is key for prognostics of stroke. As ischemic events, such as hemorrhage stroke onset happen due to rupture of blood cells, hampers the supply of oxygen to the brain tissue of the lesion area, which leads the brain cells to death. This damage to brain tissue affects the electrical activity of the corresponding local hemisphere and unstabilize the overall central nervous system. Ischemic events weaken the neuro-electrical activities, eventually, suppresses high-frequency waves (gamma or beta waves), and strengthen the low-frequency neural signal bands (alpha, theta, delta wave). A high amplitude delta wave (0.5-4 Hz) is typical in ischemic stroke [5]. Stroke also affects the symmetricity of brain waves across the left and

The associate editor coordinating the review of this manuscript and approving it for publication was Venkata Rajesh Pamula³.

right cortex. Changes in symmetric behavior of the spectral power of quantitative electroencephalography (EEG) between the two cerebral hemispheres can be described by the Revised Brain Symmetry Index (rsBSI) [6]. Studies showed that rsBSI is an important marker early prediction of stroke [3], [7].

For a detailed assessment of stroke, computed tomography (CT) and magnetic resonance imaging (MRI) are used to understand brain anatomy and to the diagnostic extent of severity of stroke of both kinds (thrombosis or hemorrhage) [8]. CT and MRI are not practical for continuous monitoring of a high-risk patient with a history of acute stroke or transient ischemic attack (Mini stroke) [9]. For the prognostics of stroke, changes in EEG can be useful in both daily life and clinical setup [10]. The real-time tracking of neural activity is the most practical way of predicting stroke onset. Studies have shown that EEG pattern changes immediately with the onset of an ischemic attack.

Numerous EEG studies have been reported where quantitative EEG measures were studied in clinical applications to evaluate the association between the EEG and the neurologic and functional outcome from ischemic stroke [7], [9], [11]–[14]. In acute stroke patients, quantitative EEG observations improve the prediction of functional outcomes in the acute stage of cerebral ischemia [15]. Delta activity and depression of alpha or beta activity are observed as a predictive marker of poor functional outcomes in the ischemic hemisphere, whereas the absence of these phenomena is observed as the case of good outcomes. In another study, it was reported that global delta power often changed over time, depending on the severity of the ischemic event [9]. In most of the earlier studies, EEG data acquisition is done with a traditional standard 10-20 EEG system with multiple electrodes. Highly trained medical staff and clinical setup are also necessary for those EEG studies. Although traditional EEG offers a noise-free brain signal, long experimental preparation time also delays the prognostics of ischemic stroke.

In summary, an ambulatory EEG system is necessary for continuous EEG monitoring in daily life setup. EEG electrodes were embedded in an eye-mask and a control module alongside would be an effective technique for portable neural activity tracking. As light affects the circadian rhythms and an eye-mask maintains a balance of light and darkness by obstructing lights, an eye-mask is generally used as a sleep wearable device for resting and sleep quality improvement. In a pilot study, Muse EEG wearables were used for the identification of stroke [3]. The rsBSI was only investigated as the marker of prognostics of stroke, other features were not explored. Neural activity monitoring using a portable EEG system was not extensively studied yet for prognostics of stroke.

SOS is recognized as a distress signal that indicates a crisis or the need for action. HealthSOS is proposed as a health monitoring system, which tracks the physiological signal of the user and provides the health status as feedback and an

alert to the emergency rescue services if stroke-predictive physiological features exceed the threshold value. HealthSOS consists of an eye-mask based ambulatory EEG, capable of emergency alert as feedback if the stroke prediction occurs.

We hypothesized that changes in the electrical activity of the central nervous system would be instantaneously detected by the portable EEG device. The signal processing and the mathematical analysis based feature extraction, the statistical analysis based feature selection, and the widely applied machine learning techniques would be a reliable method for the early prediction of stroke.

This study aims to develop the HealthSOS, an ambulatory EEG system for ischemic event prediction in daily life setup. This system was developed based on wearable EEG suitable for daily life setting, continuous data messaging to an ActiveMQ cloud server, the time-domain, and frequency-domain features extractor, Pearson correlation method for feature selection, rule-based feature extender, support vector machine (SVM) for the prediction of the stroke onset. The EEG data acquisition of the left and right brain hemispheres was done for at least 15 minutes in the awake resting state while subjects laid down on the bed attaching EEG electrodes embedded in an eye-mask on the frontal cortex. Our objective is to explore EEG indices, including rsBSI, the delta-alpha ratio, the delta-theta ratio and to evaluate the predictive features to differentiate the ischemic stroke group and the healthy control group for prognostics of ischemic stroke.

The rest of this paper is structured into six sections. Section II describes the proposed health monitoring system, followed by the experimental protocol, and the methodology used to validate the prognostic capabilities of the system. Afterward, the results are presented in Section IV, followed by the discussion. Finally, the conclusions are presented in Section VI.

II. PROPOSED HEALTH MONITORING SYSTEM

HealthSOS, a novel health monitoring system consists of a wearable EEG device, the application programming interface (API), the networking module, the signal processing module, the machine learning module, knowledgebase, the medical ontology, and the recommendation system. Details about the EEG data acquisition system, system architecture, and the health advisor system are presented in the next subsections.

A. SENSOR AND HARDWARE DETAILS

An ambulatory EEG device, designed to acquire EEG data in the resting state, consists of an eye-mask embedded electrode system and an EEG control module. As shown in Figure 1, an eye-mask has been designed with fabricated EEG and EOG (electrooculogram) electrodes. In the eye-mask, two dry gold-plated convex EEG electrodes are positioned in Frontal Fp1, Fp2 points as per EEG 10-20 system. The frontal cortex is the best-suited position for brainwave acquisition using eye-mask. The traditional 10-20 EEG system is not practical and convenient for real-time monitoring. The entire system is very light in weight and portable.

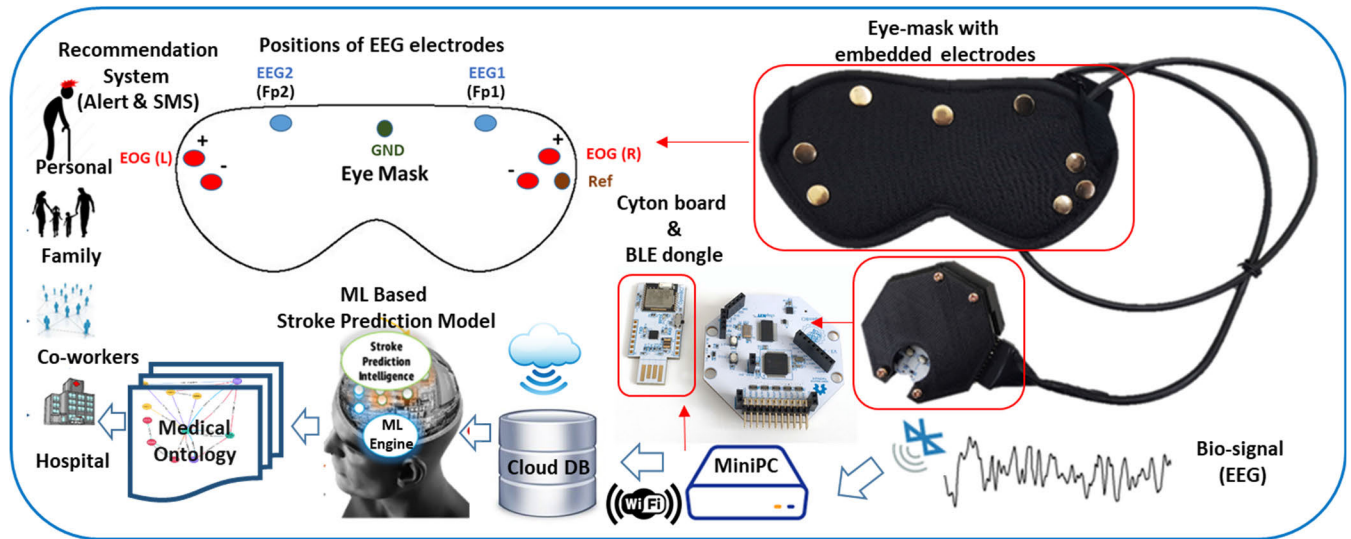


FIGURE 1. Overview of the HealthSOS system. EEG and EOG electrodes are embedded in an eye-mask. This amulatory system is developed to identify the changes in brainwave features due to ischemic stroke or other illnesses and generate recommendations and messages to rescue the patients. Electrode positions, channel descriptions and image of the newly developed portable data acquisition system are shown.

An eye-mask can be a good alternative for user-friendly brainwave acquisition. Using an eye-mask is a comparatively cheap technique with significant sleep improvements for several critical patients [16]. Eye-mask cuts off blue light, which hampers sleep. Additionally, Frontal EEG and two EOG channels can be easily fabricated in an eye-mask. The dry electrode also has limited sleep intervention compared with the wet gold-cap electrode.

B. SIGNAL ACQUISITION MODULE

A newly developed portable EEG device uses the open-source OpenBCI Cyton Board to acquire EEG signals. Cyton board consists of 8-channels bio-signal acquisition, a MicroSD slot for data storage, a Lipo battery connector, and wireless communication to a mini-computer via an RFduino radio-based USB dongle. A 3D printed enclosure was made for ease of handling of the EEG data acquisition module. EEG signals are sampled at 250 Hz sampling rate through the Cyton module. The ground was chosen on Fpz location as per 10-20 system and reference was placed a position close to the right ear. The acquisition module possesses a 3.7V battery and a DC charging module.

C. SYSTEM ARCHITECTURE AND DATAFLOW

HealthSOS, the proposed health monitoring system consists of the body-area wearable physiological sensors, the feature extraction package, feature extension package, the machine learning (ML) model, the knowledge base, the medical ontology, and the health advisor framework during sleeping and resting state. The data acquisition module sends data to the nearest mini computer (miniPC) through the Bluetooth low energy (BLE) network. A java based API was developed to read and sent EEG in JSON (JavaScript Object Notation) format. Details Specification of system architecture and dataflow for automated stroke prediction system using

HealthSOS has been shown in Figure 2. All data is sampled and sent at a sampling rate of 250 Hz. The Apache ActiveMQ protocol is used for the messaging of JSON data. The raw-data API sent brainwaves of the right and left hemisphere to web server Elasticsearch NoSQL DB through the Wi-Fi network. The context predictor predicts the user's state of activity (Resting, Sleep, Active), event information, and so on. Then, the feature extraction package is employed to extract important features, which are correlated with ischemic events, such as, Stroke. The neuro-electrical asymmetry of two hemispheres is an important predictive marker of a brain hemorrhage. The rule-based feature extender package categorizes brainwave features according to the ischemic stroke predictive features, such as the symmetry of the left and right cortexes, the ratios of spectral power. The selected brainwave features are feed to the machine learning model for training and testing of the ML model respectively. The past health records, the emergency contact information, personal details, the insurance records can be included in the profile of subscribers of the health monitoring service. The disease ontology and health advisor can recommend possible health advice to assist the patients. In the case of ischemic events such as stroke, a recommendation will be generated to attend the patient to the emergency department of the hospital for further testing, like, CT, MFI, and so on. Messages will be sent to the emergency rescue department, relatives of the patient to assist the patient to move to the nearest healthcare center.

D. FEATURE EXTRACTION AND FEATURE SELECTION

The feature extractor package comprises important neuro features both in the time domain and frequency domain. All feature extraction algorithms are implemented in java. Fast Fourier Transforms (FFT) is performed on artifact-free EEG signal with 10% hamming and extracted absolute power

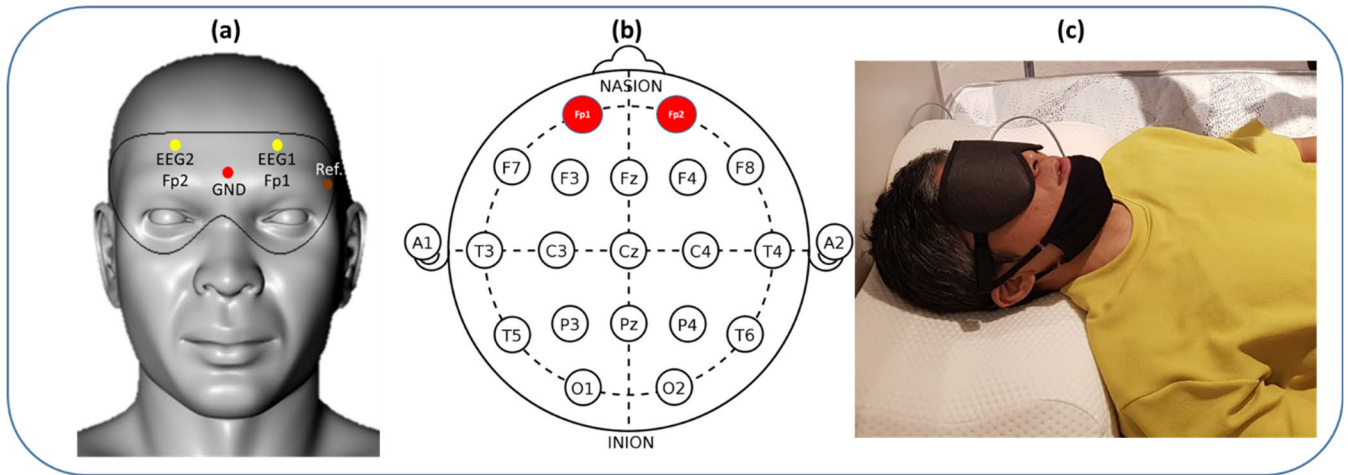


FIGURE 3. Description of device electrodes layout used in experiment (a) positions of EEG electrodes along with reference and ground electrodes in frontal cortex, (b) EEG electrodes (Fp1, Fp2) according to the standard EEG 10-20 system, (c) sample scenario of the experiment.

condition to the emergency control room or relatives to rescue and assist the patient to move to the hospital for diagnostics and treatment.

III. EXPERIMENTAL PROTOCOL

A. PARTICIPANTS OF THE EXPERIMENT

The investigation group (Stroke Patients) included 37 patients (mean age 71.6 years, 61% male) who were diagnosed with ischemic stroke. The control group included 36 healthy elderly volunteers (mean age 76 years, 28% male). Both target and control group is selected within a similar age range to reduce age-related neural activity variation. The study population consists of patients referred to Chungnam National University Hospital Rehabilitation Center, Daejeon, South Korea. Patients' ischemic stroke events were verified clinically using MRI scans or CT. The control group is composed of healthy elderly volunteers with no previous record of ischemic events or underlying known neurologic diseases. The study was approved by the institutional Ethics Committee of Korea Research Institute of Standards and Science, Daejeon, South Korea.

B. EEG DATA ACQUISITION

In this study, the EEG was acquired using the eye-mask system. Two Channels EEG were acquired. In this study, we only focus on EEG data taken on the frontal cortex. EEG electrode layout is shown in Figure 3(a). Frontal Fp1, Fp2 were chosen for brainwave acquisition as per EEG 10-20 system (Figure 3(b)). Fp1 is a representative electrode of the left hemisphere and Fp2 is a representative electrode of the right hemisphere. In the case of the stroke population, EEG data acquisition was done no later than 120 hours after admission to the emergency unit of the hospital. For this study, participants are advised not to take any drink like, Coffee or alcohol before the experiment. During EEG data acquisition, the patients were instructed to be awake, eye-closed, and in a resting (lay-down in bed) position.

Only EEG data is considered in this study and EOG data was not used in this study. Room temperature was maintained at 24° and relative humidity 40%. Participants are suggested to moisturize the forehead skin to reduce the impedance of dry electrodes. After wearing the eye-mask, data recording was delayed for five minutes to settle down participants' mental condition to resting state, and then EEG data was recorded for at least 15 minutes in the awake resting state. An example of the experimental scenario is presented in Figure 3(c).

C. PRE-PROCESSING

At first, the EEG signal is filtered out of 60 Hz AC noise (Local 60 Hz power grid). The built-in notch filter cut-off the 60 Hz noise in the OpenBCI Cyton. EOG artifacts are filtered from the EEG signal.

D. FEATURE EXTRACTION

EEG delta (δ) wave, theta (θ) wave, alpha (α) wave, and beta (β) wave, Gamma (γ) wave are extracted from the artifact-free EEG signal. Various EEG features are measured over an epoch length of 10 seconds to understand the power in the EEG bands. Signal transformations, such as Lyapunov exponent, central moment, time-delayed mutual information, skewness, spectral slope, capacity dimension and correlation dimension, correlation coefficient, and so on; have been applied to evaluate the unique EEG features.

1) REVISED BRAIN SYMMETRY INDEX

The Revised Brain Symmetry Index is an efficient marker for continuous EEG monitoring for hemispheric stroke and computed according to the methods suggested by Van putten [6]. As hemispheric stroke causes a lack of neuro-electrical balance between the right and left hemispheres, rsBSI may allow early prediction of stroke [3], [7]. The rsBSI is a numerical value ranging between zero (absolute symmetry) and one (complete asymmetry).

2) THE RATIO OF DELTA-ALPHA AND DELTA-THETA POWER

The ratio of delta power and alpha band power was computed to measure the DAR (delta-alpha ratio). The ratio of delta power and theta band power was defined as the delta-theta ratio (DTR). EEG spectral band power ratios (DAR and DTR) are important markers of cognitive change due to stroke [11].

3) BAND POWER ASYMMETRY INDEX

Spectral Band power asymmetry Index is the relative difference of each band power between two brain hemispheres, such as frontal alpha asymmetry, frontal beta asymmetry, and so on. EEG spectral band asymmetries are found to be related to depression, epilepsy, apnea, and so on [20], [21].

4) LYAPUNOV EXPONENT

Lyapunov exponent gives a measure of the chaotic nature, the divergence or convergence of EEG signal. It is also used to estimate the production of entropy in the EEG waveform. Analysis of the Lyapunov exponent of EEG was studied to classify the Schizophrenia, neurological disorder patients, and the control population [22].

5) KURTOSIS

Kurtosis gives information on whether EEG data is light-tailed or heavy-tailed compared with a normal distribution, also the size of the “tails”.

6) CENTRAL MOMENT

Central Moment computes deviations from the mean instead of from zero within the selected EEG signal. The central moment feature of EEG frequency bands can be implemented to detect epileptic seizures [23].

7) TIME-DELAYED MUTUAL INFORMATION

Mutual Information determines the relevance and redundancy of the neuro-electric signal given a time delay. Study shows that time-delayed mutual information of EEG and EMG (Electromyography) of active movement is significantly different from passive movement [24].

8) SKEWNESS AND PEAK-PEAK

Skew is a measure of the degree of asymmetry in an epoch of an EEG waveform [25]. Peak-Peak (P-P) measures the distance between the maximum and minimum peak value in an epoch.

9) SPECTRAL SLOPE

The spectral slope or gradient measures the non-standard regression coefficient and gives information about the direction and steepness of the waveform. The spectral slope of EEG gives a reliable estimate of neurological disorders, such as neonatal seizures [26].

10) CAPACITY DIMENSION & CORRELATION DIMENSION

Capacity Dimension and Correlation Dimension are the fractal dimensions that indicate the extent of changes in the detail of a waveform with the change in scale. Fractal dimension is found effective to detect the EEG changes in an epileptic seizure, a bipolar disorder, behavioral micro-sleep, and so on.

11) CORRELATION COEFFICIENT

Correlate provides the linear correlation between the two variables and has a value ranging from 1 to -1. EEG linear correlation-coefficient is considered as an effective measure of the activity of the neural network of the cortical region [27].

E. DATA ANALYSIS

EEG frequency bands (alpha, beta, theta, delta, gamma) are extracted using fast Fourier transforms. Several frequency bands' features, such as relative power, mean power, mean frequency, median frequency, peak frequency, spectral edge, and so on, are calculated. Descriptive statistics and independent-samples t-test are carried out. Statistical analyses were performed using SPSS 24 software (IBM, Armonk, New York). Feature selection is executed to rank EEG features based on the measurement levels of the target. Pearson's chi-square test computed the feature importance calculated as $(1-p)$, where p is the p -value of the statistical test of association between the feature and the target group (stroke group or control group). Then selected best feature sets from the training dataset is feed to the supervised machine learning models to obtain the classification models, which are later used for testing the datasets. Machine learning analyses were performed using IBM SPSS Modeler 18 software (IBM, Armonk, New York).

IV. RESULTS

A. STATISTICAL ANALYSIS

Independent-samples t-test was performed to compare the means of EEG features for two groups, which provides Levene's test for equality of variances along with both equal and unequal-variance t values for the difference in means. A p -value of less than 0.05 was considered statistically significant. In the following subsections, the results of significantly important features will be explored only.

1) RESULTS OF THE REVISED BRAIN SYMMETRY INDEX

The Revised Brain Symmetry Index of the stroke and healthy control groups was evaluated based on EEG in the brain frontal lobe at Fp1, Fp2 positions. Figure 4(a) shows the statistical distribution of rsBSI of the stroke and control group. The mean and standard deviation of rsBSI for the stroke group 0.263 and 0.088 respectively. On the other hand, the mean and standard deviation of rsBSI for the control group 0.143, and 0.053 respectively. In Levene's statistical test of the equality of variances between the two groups, the significance value is $p < 0.0001$, which implies that the two groups don't

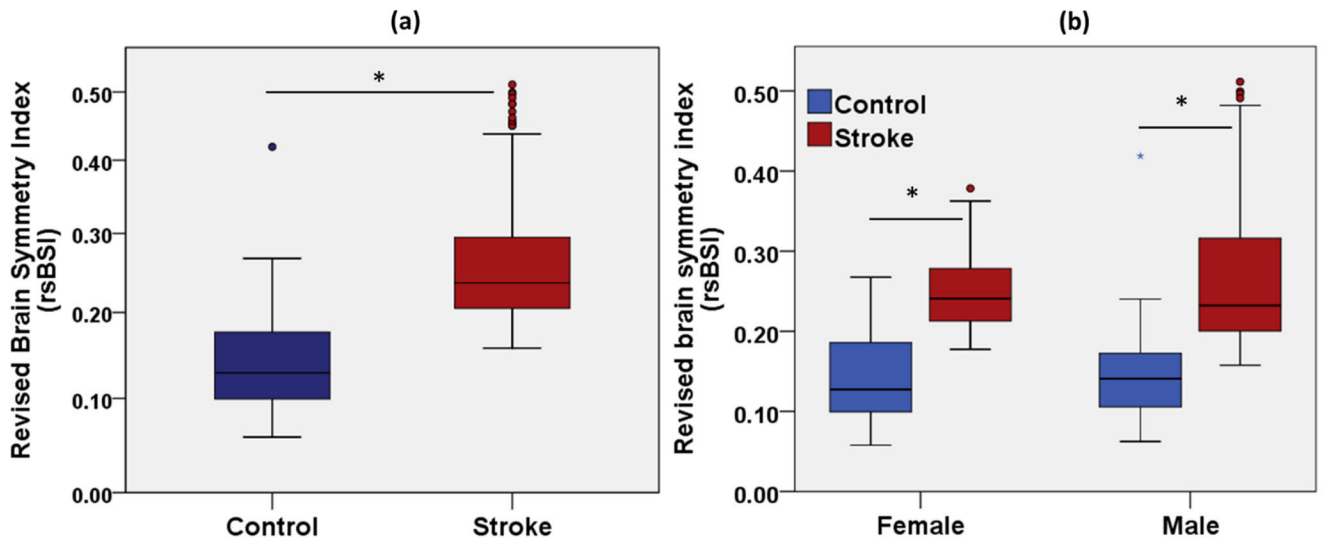


FIGURE 4. Median and interquartile range of rsBSI computed in the frontal scalp among (a) the stroke patient population and the control population, and (b) the male group and female group of the stroke patient population and the control population. * $p < 0.0001$. *($p < 0.0001$) indicates significant difference.

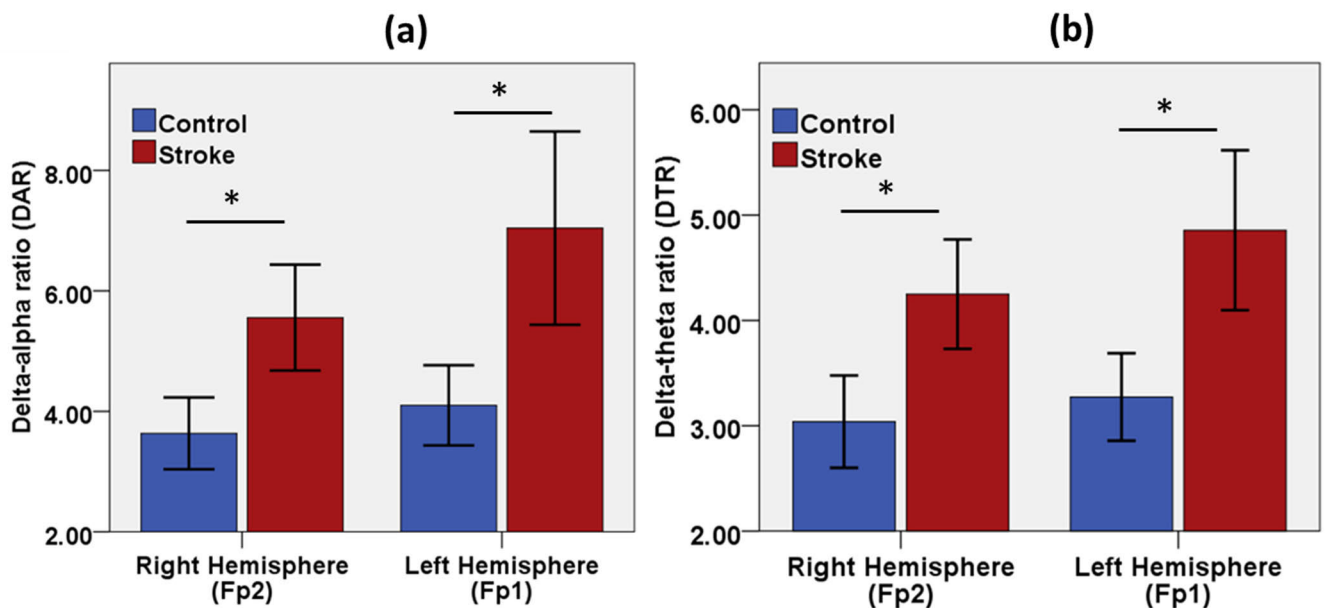


FIGURE 5. Mean and error bar of (a) DAR, * $p < 0.0001$ in Fp1,* $p < 0.0005$ in Fp2 (b) DTR, * $p < 0.005$ computed in the frontal electrodes Fp1, Fp2 among the stroke patient population and the control population. Error bar shows 95% confidence interval. * indicates significant difference.

have equal variances. In the t-test for equality of means, the t-statistic is 17.656 with 446 degrees of freedom. The corresponding two-tailed p-value is $p < 0.0001$. As a result, it can be concluded that the difference of means of rsBSI between the stroke group and the control group is different between each other. A higher revised brain symmetry index indicates the neural impairment in one-side of the hemisphere. A similar finding is observed in other EEG electrode positions of the stroke population using a short EEG recording [3], [28]. Van putten used prolonged 12-24 hours EEG monitoring of the stroke patients to understand the correlation between rsBSI and the stroke events [7], [12]. Blood flow to

brain tissue is hampered due to ischemic hemorrhage. Brain cell damage impairs the electrical activity of the corresponding brain hemisphere. Eventually, a stroke onset alters the normal symmetric characteristic of left and right hemispheric EEG. As Fp1 and Fp2 are the representative positions of the left and right hemispheres respectively, larger rsBSI variation between Fp1 and Fp2 can be used as an effective indicator of detection of ischemic events, such as stroke. Figure 4(b) shows the rsBSI score of the stroke and control group for the male and female populations. rsBSI of the male stroke group has a wider interquartile range compared with that of the female stroke group. On the other hand, the median rsBSI

(0.23) of the male stroke population is slightly lower than that (0.24) of the female stroke population.

2) RESULTS OF DELTA-ALPHA AND DELTA-THETA RATIO

Figures 5(a) and 5(b) show the statistical means of frontal EEG DAR and DTR for the stroke and control group. The mean of DAR and DTR for stroke group 5.556 and 4.250 respectively in Fp1 and 7.043 and 4.856 respectively in Fp2. On the other hand, the mean of DAR and DTR for the control group 3.634 and 3.040 respectively in Fp1 and 4.10 and 3.273 respectively in Fp2. The independent group t-test is performed to compare the means and variances of DAR and DTR between the two groups. In Levene's statistical test of the equality of variances of DAR between the two groups, the significance value is $p < 0.0001$ in Fp1, $p < 0.0005$ in Fp2 which implies that the two groups don't have equal variances of DAR. In Levene's statistical test of the equality of variances of DTR between the two groups, the significance value is $p < 0.005$ in Fp1, Fp2 which implies that the two groups don't have equal variances of DTR. In the t-test for equality of means of DAR, the t-statistic is 3.59 with 446 degrees of freedom in Fp1 and 3.39 with 446 degrees of freedom in Fp2. Besides, in the t-test for equality of means of DTR, the t-statistic is 3.52 with 446 degrees of freedom in Fp1 and 3.65 with 446 degrees of freedom in Fp2. The corresponding two-tailed p-value is $p < 0.0005$ for DAR in Fp1 and Fp2 respectively, 0.0005 for DTR in both Fp1 and Fp2. As a result, it can be concluded that the difference of means and variances of DAR, DTR of the stroke group and the control group are different from each other.

3) RESULTS OF THE CORRELATION COEFFICIENT, KURTOSIS, SKEWNESS, SPECTRAL SLOPE

Figure 6(a) shows the statistical means of the correlation coefficient of EEG frequency bands (alpha, beta, theta, delta, gamma) for the stroke and control groups. In the results of the correlation coefficient, a significant difference ($p < 0.05$) was observed in the means of correlation coefficients of all bands in Fp1, but no significant difference was observed in the variances of correlation coefficients.

Figure 6(b) shows the statistical means of the kurtosis of EEG frequency bands for the stroke and control groups. In the results of the kurtosis analysis, a significant difference ($p < 0.05$) was observed in the variances of kurtosis of alpha, beta, and gamma bands in Fp2, but no significant difference was observed in the means of kurtosis.

Figure 6(c) shows the statistical means of the spectral slope of EEG frequency bands for the stroke and control groups. In the results of the slope, a significant difference ($p < 0.05$) was observed in the means of the slope of alpha, beta, and gamma bands in Fp1, but no significant difference was observed in the variances of the slope.

Figure 6(d) shows the statistical means of the skewness of EEG frequency bands for the stroke and control group. In the results of the skewness, a significant difference ($p < 0.05$) was observed in the means of skewness of theta and gamma

bands in Fp1, but no significant difference was observed in the variances of skewness.

B. MACHINE LEARNING ANALYSIS

All EEG features with feature importance of a p-value greater than 0.95 have been chosen for the classification analysis. A total of 48 features are selected out of 274 initial extracted brainwave features based on feature importance ($p > 0.95$). To evaluate classification accuracy, ROC (Receiver operating characteristic) curve is the most effective tool. AUC (Area under the curve) is a classification performance predictor and defined as the area under the ROC curve. The nearer the AUC is to 1.0, the better the performance of the model. Besides, the Gini coefficient is an alternative measure to the AUC and is defined as the Gini Coefficient, which is two times (AUC-1), ranging between 0 and 1. The confusion matrix or error matrix provides a clear picture of classification performance. From the confusion matrix, several other performance parameters, such as accuracy (ACC), sensitivity (true positive rate), specificity (true negative rate), precision (positive predictive rate), negative predictive value, AUC, and Gini coefficient are calculated. The accuracy was calculated as the ratio of correct prediction to the total observations and considered as the most intuitive performance measure to identify the best model. Precision is the ratio of correct positive prediction to the total predicted positive observations. Sensitivity is the ratio of correct positive prediction to all the actual observations. Specificity is the ratio of correct negative prediction to all the actual observations. The performance evaluation parameters are computed using the following standard formulas:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Negative predictive value (NPV)} = \frac{TN}{TN + FN}$$

$$\text{Accuracy(ACC)} = \frac{TN + TP}{TN + TP + FN + FP}$$

where TP stands for the true positive, TN means the true negative, FP stands for the false positive, and FN means the false negative. All the performance measures for the training datasets and the testing datasets are listed in Table 1 and Table 2 respectively.

As listed in Table 1, SVM classified the training dataset with the highest AUC (98%), highest accuracy (ACC: 93%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of SVM are 98%, 88%, 89%, 98%, 98%, and 95%, respectively. Discriminant analysis classified the training dataset with the lowest accuracy (ACC: 88%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of Discriminant analysis are 91%, 86%, 86%, 90%, 96%, and

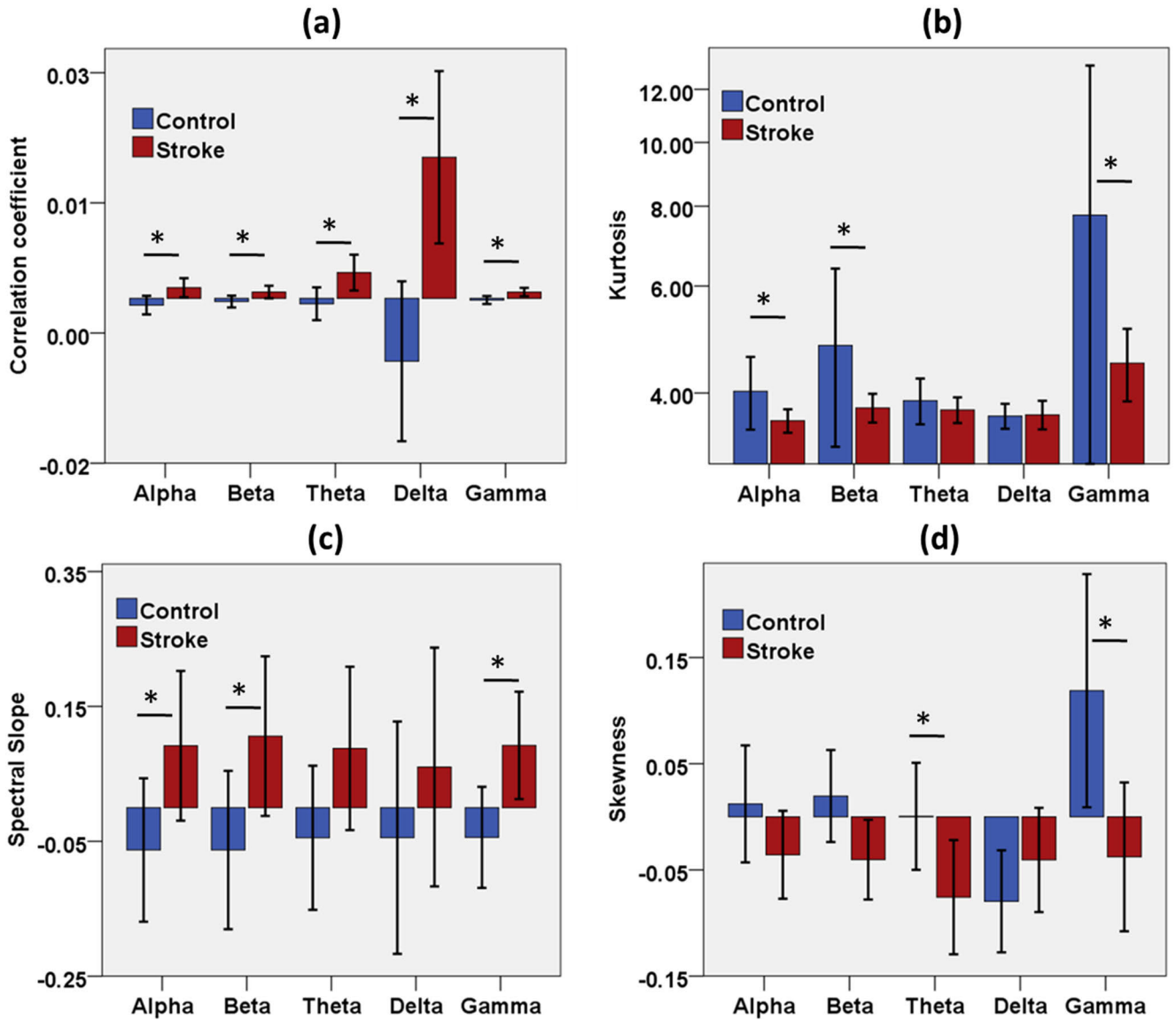


FIGURE 6. Mean and error bar of (a) the correlation coefficient in Fp1, $*p < 0.05$ (b) kurtosis analysis in Fp2, $*p < 0.05$, (c) spectral slope in Fp1, (d) skewness in Fp1 computed among the stroke patient population and the control population. Error bar shows 95% confidence interval. $*(p < 0.05)$ indicates significant difference.

TABLE 1. Results of the classification performance of different models using the training dataset.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	AUC (%)	Gini (%)
SVM	93	98	88	89	98	98	95
Discriminant	88	91	86	86	90	96	92
Neural Network	90	86	94	94	87	96	93
QUEST	93	94	93	93	94	95	91
C&R Tree	92	98	86	87	98	92	84

92%, accordingly. QUEST classified the training dataset with moderate accuracy (ACC: 93%). The sensitivity,

specificity, precision, negative predictive value, AUC, Gini coefficient of QUEST are 94%, 93%, 93%, 94%, 95%,

TABLE 2. Results of the classification performance of different models using the testing dataset.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	AUC (%)	Gini (%)
SVM	89	94	84	84	94	97	95
Discriminant	87	87	86	85	88	94	88
Neural Network	88	88	88	87	89	92	84
QUEST	91	90	93	92	91	94	88
C&R Tree	89	94	84	84	94	89	78

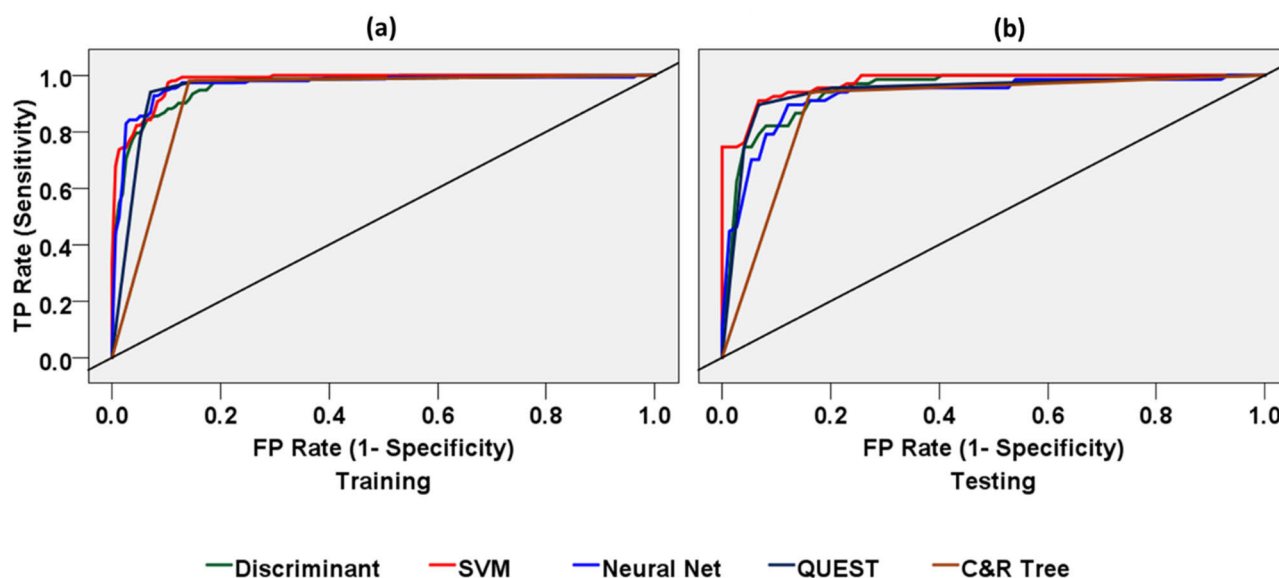


FIGURE 7. Receiver Operating Characteristic (ROC) curves for five different machine-learning models (Discriminant analysis, Support Vector Machine, Neural Network, QUEST, C&R Tree). Area under ROC curve (AUC) is an indicator of prediction accuracy. (a) ROC curve of the training dataset. SVM classified the training dataset with the highest AUC (98%) and highest accuracy (ACC: 93%); (b) ROC curve of the testing dataset. SVM classified the testing dataset with the highest AUC (97%) and moderate accuracy (ACC: 89%). Diagonal black line is the reference line.

and 91%, sequentially. C&R Tree classified the training dataset with moderate accuracy (ACC: 92%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of C&R Tree are 98%, 86%, 87%, 98%, 92%, and 84%, successively. The neural network classified the training dataset with moderate accuracy (ACC: 90%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient are 86%, 94%, 94%, 87%, 96%, and 93%, consecutively. ROC (Receiver operating characteristic) curves of the ML models using the training dataset are shown in Figure 7(a).

According to Table 2, SVM classified the testing dataset with the highest AUC (97%) and moderate accuracy (ACC: 89%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of SVM are 94%, 84%, 84%, 94%, 97%, and 95%, respectively. Discriminant analysis classified the testing dataset with the lowest accuracy (ACC: 87%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of Discriminant

analysis are 87%, 86%, 85%, 88%, 94%, and 88%, consecutively. QUEST classified the testing dataset with the highest accuracy (ACC: 91%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of QUEST are 90%, 93%, 92%, 91%, 94%, and 88%, sequentially. C&R Tree classified the testing dataset with moderate accuracy (ACC: 89%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of C&R Tree are 94%, 84%, 84%, 94%, 89%, and 78%, accordingly. The neural network classified the testing dataset with moderate accuracy (ACC: 88%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient are 88%, 88%, 87%, 89%, 92%, and 84%, in succession. ROC (Receiver operating characteristic) curves of the ML models using the testing dataset are shown in Figure 7(b). Overall, SVM shows the highest accuracy (ACC: 92%), the highest AUC (98%), and the highest Gini coefficient (95%). Statistical agreement between stroke predictions by the above five models is 84%.

V. DISCUSSION

In our study, we aimed to characterize the electrical activity of the frontal lobes through ambulatory EEG data acquisition of newly diagnosed stroke patients and healthy adults to find out the features showing the effective indication of the brain injury due to stroke events. The frontal lobes are critical for cognitive processes and are easily accessed by the wearable EEG device. Specific EEG band power is associated with the specific functional outcome of the brain and in the case of ischemic stroke, is linked to the degree of neural damage in the lesion area of the brain. The outcome of this study also adds to our understanding of abnormal hemispheric asymmetry in homologous channel pairs (Fp1 and Fp2), which represent the most prominent marker of the human awake resting-state EEG in the stroke impaired brain.

The result of rsBSI showed a statistically significant difference between the stroke patient group and the control group. Our findings match with previous studies revealing that the stroke patients group possesses a higher rsBSI value compared with the healthy control group [6], [7], [12], [29]. Stroke hampers the blood flow to brain tissue, which leads to damage to brain cells and creates a lesion. A higher rsBSI value indicates the lack of interhemispheric neuro-electrical balance due to the presence of the lesion caused by the ischemic stroke. Lower rsBSI correlates with a healthy brain for the absence of lesions [3].

According to this study, resting DAR and DTR, resulting from the relative-band power of the delta, theta, and alpha, are significantly important markers to classify the stroke group and the healthy control group. Higher delta power is observed in the electrodes of the pre-frontal positions after stroke [11], [30]. The alpha activity is significantly lower in the stroke population than in the healthy adult population. Relative alpha power is a less informative predictor for the monitoring and assessment of the ischemic stroke [11], [13]. Some studies from combined EEG, MFI, CT observations suggest that alpha attenuation and slowing reflect brain injury while delta activity rise is indicative of sub-cortical injury [5]. Beta activity is observed to be similar in the stroke group and the control group. Relative Beta power is considered as a less effective predictor and no reported statistically significant difference is found between the beta activity of the stroke patients and the healthy adults [5], [13]. Theta activity was also observed to have the potential to discriminant between the stroke population and the healthy control population [31]. DAR is considered the most reliable EEG feature for the prognostics of the ischemic stroke [11], [12], [14]. The DTABR, defined as the ratio of the sum of delta and theta to the sum of alpha and beta, similar to DAR is another informative predictor of Ischemic stroke. In the current study, DAR is calculated individually in two frontal electrodes. In both electrodes, DAR showed a significant difference between the stroke group and the healthy control group. Besides, as most of the stroke patients have left-side lesions, delta activity is lower on the lesion side and higher on the healthy side of the brain. So, DAR is higher in the Fp1 electrode than

the Fp2 electrode. Few studies identified DTR as a potential marker of cognitive outcome after stroke [11]. Higher resting theta activity is associated with the healthy cognitive performance [32]. Lower resting theta power or higher DTR is a predictor indicator of impaired post-stroke cognitive outcome. A similar trend is observed in the DTR of the frontal electrodes in this study. DTR showed a significant difference between the stroke population and the healthy adult population. A rise in delta power, DAR, DTR is associated with the impaired neural functional outcome resulting from stroke. Resting DAR and DTR were also shown to correlate with cognitive outcome following stroke [11], [33].

EEG correlation-coefficient is an informative indicator of interhemispheric connectivity patterns. Ischemic stroke patients' clinical outcome is associated with the change of delta power [33]. In our study, a significant correlation is observed between stroke patients and all EEG bands' power. The kurtosis and spectral slope of alpha, beta, and gamma were observed as a statistically significant indicator of ischemic stroke. Other parameters did not show significant important differences.

In this study, Discriminant analysis, SVM, Neural network, QUEST, and C&R tree have been used to classify stroke patients and healthy control subjects. Good statistical agreement (84%) is observed between stroke predictions by the above five models. Overall, SVM shows the highest accuracy, the highest AUC, and the highest Gini coefficient. SVM is a benchmark machine learning technique as well as proven to show good results in multi-class classification to discriminate stroke patients and healthy control subjects using EEG signal [34], [35]. Though the computational period of the SVM model is longer, the SVM model seems to be the most accurate model to predict stroke prognostics.

To the best of our knowledge, our developed HealthSOS is the first to utilize wearable EEG fabricated on an eye-mask for stroke prognostics purposes. Past several studies used a standard 10-20 EEG system with around 16-32 channels. For real-time health monitoring in daily life activities, such as, resting, sleeping, EEG along with multiple wires and conductive gel can't be a practical solution. So, our portable can be a good alternative for traditional EEG. HealthSOS may be used as an alternative to the traditional sleep study. It is worth noting that our system can also be used as a measure for the prediction of wake-up stroke in an overnight sleep setup. Another potential application of the proposed portable system is the sleep monitoring system.

In this study, we focused on only the frontal lobe for understanding changes of EEG for neural impairment due to the ischemic stroke, not the entire cortex. Although the frontal lobe has a high resemblance to other lobes, there still exist specific cognitive and functional outcomes on each cortical lobe. For this reason, the model developed here generalizes to only the frontal lobe with current parameterization. Although EEG and EOG data can be acquired using the HealthSOS device, we only considered EEG for analysis for the study of the stroke population. Eye movement is significantly

important for sleep quality and REM (Rapid Eye movement) sleep. In the future, EEG and EOG both can be utilized in an automated sleep performance and stroke prognostics study.

VI. CONCLUSION

HealthSOS, a portable low-cost eye-mask based EEG system was developed here, which could be used for prognostics of ischemic stroke and change of functional outcome due to stroke. Details of the hardware, API dataflow, description of the extracted features, the stroke prediction based on machine learning are presented. Our system has been successfully validated with 37 stroke patients and 36 healthy volunteers. rsBSI, the delta-alpha ratio, the delta-theta ratio were found as statistically significant markers for the prediction of ischemic stroke. HealthSOS system is expected to be a potential health-care assistance system for prognostics of ischemic stroke outside the clinical environment.

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