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Cyber Physical System for Stroke Detection

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ABSTRACT Stroke is one of the fatal diseases that affect the brain and causes death within 3 to 10 h. However, most of the deaths caused by a stroke can be avoided with the identification of the nature of stroke and react to it in a timely manner by intelligent health systems. The state-of-the-art cyber-physical systems (CPS) enable interaction between physical and computational world to identify any anomaly in the physical world and respond to it. The response of CPS may vary depending upon the context of the physical world. Extensive research has been done in this area from the perspective of wireless sensor networks, body area networks, and wearable smart devices. This paper proposes a CPS for detecting the occurrence of stroke in patients, who have a high risk of stroke or have survived a stroke before. The developed CPS sends recorded data to the doctor and alerts him when the stroke occurs. The proposed system is operating on data acquired from electroencephalography sensors from patients' brain. This article aimed at decreasing human mortality rate due to stroke and will bridge the gaps in CPS due to interdisciplinary isolation. The disciplines involved in the development of a CPS include communication networks, pattern recognition, software engineering, mathematics, and biomedical.

INDEX TERMS Cyber-physical system (CPS), stroke, electroencephalography (EEG), brain waves.

I. INTRODUCTION

Currently, the global population is facing a serious problem of increasing healthcare issues. One of the major issue is the emergence of Non-Communicable Diseases (NCDs) i.e., diseases that do not pass from person to person. NCDs include cardiac diseases, asthma, epilepsy, and stroke. More than 63% of global deaths are caused by NCDs and number of deaths will rise to 75% by 2020 [1]. Statistics show that 2,400 American die every day due to cardiac arrest [2]. Approximately 60 million people in the world suffer from epilepsy [3]. Eighteen million American are diagnosed with chronic respiratory diseases and over 10 million remain undiagnosed [4], [5].

Stroke, also commonly referred to as Brain Attack, is caused by the lack of blood supply to some parts of the brain. The blood supply may have been disturbed either due to blockage of blood in the vessels inside the brain or due to bleeding inside the brain. In the United States, the stroke is reported to be the fourth most heinous killer. The US national budget 2008, for stroke, was $18.8 billion [6]. Mortality rate due to stroke in Pakistan was reported to be up to 0.1 million in 2004 [7]. The mortality rate is expected to be doubled by 2020 [8]. However, the mortality rate due to stroke can be reduced if the stroke is diagnosed at an early stage of its occurrence [1]. It is approved by U.S Food and Drug Administration (FDA) that the stroke patient should be injected with intravenous tissue plasminogen activator (IV tPA) as quickly as possible. tPA significantly improves chances of survival from stroke if it is injected within 3 hours after the occurrence of stroke [9]. Therefore, the initial hours after the stroke occurrence are crucial. Several national awareness programs have initiated the mission to aware the public and general physicians about the emergency of stroke [10]. Despite the efforts of public awareness programs, there still exists a significant delay in patient arrival at the hospital after stroke [11]. A telehealth care system that can identify the stroke at its early stage can fill this gap.

The state-of-the-art cyber systems enable interaction between physical and computational world to identify any anomaly in the physical world and respond to the anomaly. In case of identifying the disease in the human body, the interaction is between the intelligent system and the human body. The cyber systems are capable of monitoring human health by considering the symptoms of chronic diseases that include blood pressure, blood sugar level, temperature, cardiovascular activities (ECG), and neural impulses (EEG) etc. EEG (Electroencephalography) is defined as the measure of electric potentials on the scalp surface using electrodes [12]. EEG is most widely used in Intensive Care Unit (ICU) to monitor brain functions of normal as well as affected people. For instance, continuous EEG in ICU can help detect seizures that may be missed in unconscious and paralyzed patients [13].

Below, in Section II, a detailed overview about the Stroke is presented with a brief introduction about EEG features related to stroke. Section III presents the detailed methodology including pre-processing of EEG recorded data, an algorithm for extraction of stroke-related EEG features and an in-depth analysis of various techniques and classification methods, available for detecting stroke with the help of EEG. Section IV describes the implementation of the proposed Cyber Physical System and communication protocols for the interaction of CPS components. Section V presents the results of individual EEG features and their classification. Finally, Section VI, concludes the paper with a discussion.

II. BACKGROUND STUDY

A. STROKE

A person undergoing a stroke attack can feel an abrupt numbness in either left or right side of the body. Difficulty in speech, abrupt vision problem, loss of balance and dizziness are also visible symptoms, associated with stroke [14]. Different parts of the brain, control different body areas, therefore visible symptoms of stroke depend upon the part of the brain affected by stroke. Some people might feel pain or sometimes it can be completely painless. That is the reason why stroke is often misjudged by patients. Stroke is classified into two different types based on the reason of the reduced amount of blood supply to the brain which is also termed as Cerebral Blood Flow (CBF).

1) ISCHEMIC STROKE

This is the most common type of stroke. Almost 80% of strokes are classified as ischemic stroke [15]. It is caused by blockage of a blood vessel by a blood clot. As a result, some area of the brain is deprived of oxygen and nutrients causing the damage to neurons. The longer the duration of blockage, the more is the damage. Within a matter of minutes, the blockage results in the complete death of neurons and thus causing a permanent damage to the brain. Stroke is therefore considered as a severe medical emergency. There are further two subtypes of ischemic stroke: thrombotic and embolic. The former occurs when the blood clot is formed in the blood vessels of the brain. Narrowing of blood vessels due to an increased level of cholesterol can result in thrombotic ischemic stroke. The later occurs, due to a clot formed in the heart which then travels to the brain through arteries and causes blockage of blood supply. This type is associated with cardiac arrest, malfunctioning of cardiac valves or irregularity in a heartbeat.

2) HEMORRHAGIC STROKE

This type of stroke is caused when a blood vessel suddenly raptures and causing blood to leak. This is mostly caused by increased blood pressure. Other less common causes include head injury, tumors, infections and blood clotting. This article focuses only on Ischemic Stroke.

B. ELECTROENCEPHALOGRAPHY (EEG) OF STROKE

Neurons in the brain communicate with each other by releasing neurotransmitters. The communication of neurons creates the magnetic and electric field. The activity of an individual neuron is not adequate to generate enough potential on the scalp for measurement. EEG is a measure of potential that is caused by a population of neurons communicating simultaneously [16]. EEG is widely used in ICU's to analyze functional changes in brain activity for detecting various diseases. Evidence from several studies have shown a positive correlation between power measures of specific frequency bands and neural states. A typical bed-side EEG recording machine consists of a number of electrodes (usually 24), an amplifier and noise canceler interfaced with a computer. EEG signals are divided into five major frequency bands depending upon their association with different human activities or behaviors [17].

Cyber Physical Systems (CPS) are defined as the systems that integrate the physical world with the computational world using sensor(s) and networking technologies [18]. CPS's in telehealth care involve sensing the physiological parameters from human body such as temperature, blood pressure, insulin level etc., and performing classification of diseases. Electroencephalography (EEG) is most commonly used technique for diagnosing neural diseases such as stroke, epilepsy, Alzheimer's disease and schizophrenia etc.

C. BRAIN SYMMETRY

The measure of the difference in average spectral power of the left and right hemisphere of complete EEG spectrum (1-25GHz) is called Brain Symmetry Index (BSI) [19], [20]. BSI of a normal person is zero, because of symmetry in both hemispheres. Whereas, it is 1 for a completely abnormal person (having a severe stroke) [19]. BSI of each electrode pair was studied separately in [21]. This method was used for analysis of EEG of 110 subjects in Oxford Community Stroke Project (OCSP). Pairwise BSI was found to be more closely associated with stroke than the global BSI of all electrodes.

Michelson *et al.* [22] have classified 31 Ischemic Stroke patients using Structural Brain Injury Index (SBII). The SBII has been very accurate in the identification of brain trauma. EEG data includes recordings from FP1, FP2 and F7 and F8 electrodes. The classification resulted in 91.7% of precision and 90.3% recall.

D. POWER OF EEG SUB-BANDS

The brain receives necessary nutrients and oxygen through fresh blood from lungs and heart. Stroke is caused when some part of the brain does not receive sufficient amount of oxygen and nutrients due to lack of blood supply. The supply of blood to the brain of a normal adult is approximately 750 milliliters per minute. It is the highest percentage of cordial output required by any organ in the human body [23]. We will refer to the blood supply to the brain as Cerebral Blood Flow (CBF). Fig. 1 depicts the changes in EEG due to a decrease in CBF. It is shown that when the CBF is reaching minimum threshold (i.e. less than 10-12 ml/100gm.min) the neurons start dying.

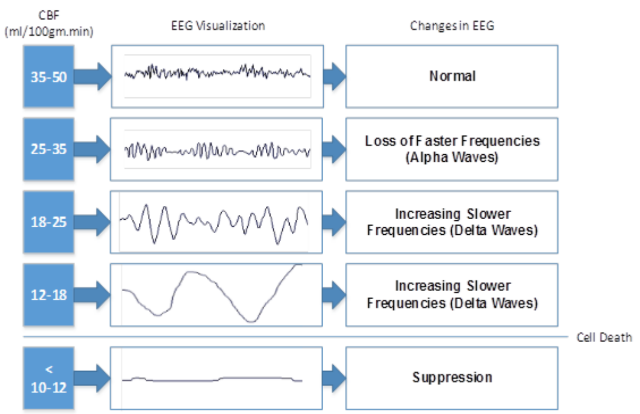

FIGURE 1. Variations in EEG with changes in cerebral blood flow.

EEG of 20 subjects was analyzed using Fourier-Transform and a strong correlation of Cerebral Blood Flow (CBF) was observed with the Delta wave power [24]. A reduced Alpha power and increase in delta power are found to be associated with severity of ischemic stroke. Delta power is supposed to be the strongest predictor of ischemic stroke [25]–[33]. All the studies related to any sub-band power of EEG signal mentioned earlier are calculated for each channel separately. However, due to the symmetry of brain left and right hemisphere, the power indices involving comparison of left and right hemisphere can be more accurate [34].

Omar *et al.* [35] have used the Relative Power Ratio (RPR) of EEG recordings of 22 ischemic stroke patients to rank the patients in accordance with their severity of stroke. RPR is the power of left hemisphere and right hemisphere of a sub-band divided by the sum of powers of all sub-bands.

The work was later extended in [36] and used the data of 100 subjects. The subjects were divided into three groups based on the level of physiological support required by the subjects. Group 1 contained 33 subjects, group 2 contained 31 subjects and group 3 contained 36 subjects. Unequal division of the patients leads to biased classification. The authors then used k-NN classification to classify EEG data of ischemic stroke patients. The proposed features for the classification included maximum Power Spectral Density (PSD), Relative Power Ratio (RPR), mean and standard deviation of all sub-bands (i.e., Delta, Theta, Alpha, Beta, and Gamma). For the value of k=5, the accuracy of the proposed system is 80% using the test data and 85% of the training data. The same author further extended his work and used Artificial Neural Network (ANN) based on only one feature i.e. RPR [37]. The accuracy of the system using ANN was 98%, which is a significant improvement from kNN based system. State-of-the-art research in the area of stroke detection is summarized in Table 1.

TABLE 1. Units for magnetic properties.

	Feature	Classifier	Precision	Recall
SBII Based System	Structural Brain Injury Index	SVM	91.7%	90.3%
K-NN Classifier based System	Relative Power Ratio	KNN	100%	95%
ANN-based System	Relative Power Ratio	ANN	100%	98.8%

III. METHODOLOGY

Quantitative EEG is used to perform computational analysis of EEG signals. State-of-the-art hospitals and neurology centers are now equipped with bed-side QEEG devices. The proposed CPS is based on wearable wireless QEEG device, which is now commonly available, to record the EEG in real-time and process it to detect the occurrence of stroke. Fig. 2 presents the architecture of the pro-posed CPS for stroke detection. The following sub-sections discusses each component of the proposed CPS in detail.

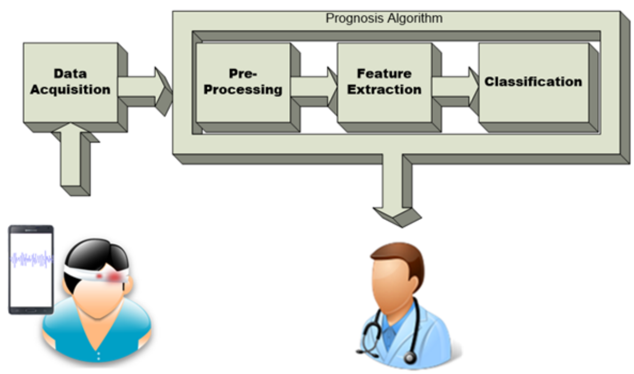

FIGURE 2. The architecture of the proposed cyber physical system.

A. DATA ACQUISITION

EEG of the scalp provides rich indications about the underlying activity of the brain. EEG signal of the brain is communicated to the EEG recording device via electrodes. Data acquisition for this research followed the globally recognized standard electrode placement system (10/20 system) as shown in Fig. 3.

Each electrode is named according to its location on the scalp. Letter associated with the electrodes represent their respective positions. The letters P, C, T, O, and F represent

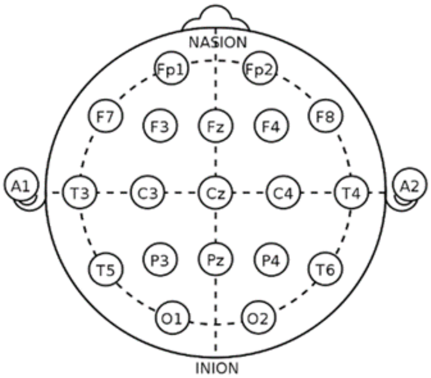

FIGURE 3. Location of electrodes in 10/20 system.

the Parietal, Central, Temporal, Occipital, and Frontal lobes respectively. The even numbers with the electrode letters represent the right hemisphere, whereas the odd numbers represent the left hemisphere of the brain. Letter 'z' is associated with the center column of electrodes. EEG signal is characterized by its amplitude and frequency bands. The amplitude of EEG recorded on the surface of scalp ranges from 20μV to 100μV and frequency ranges from 0.5Hz to 38Hz.

The dataset of EEG used in this article was obtained from Shaheed Mohtarma Benazir Bhutto Medical University, Larkana, Pakistan. The data of 15 ischemic stroke patients and 15 normal subjects were recorded.

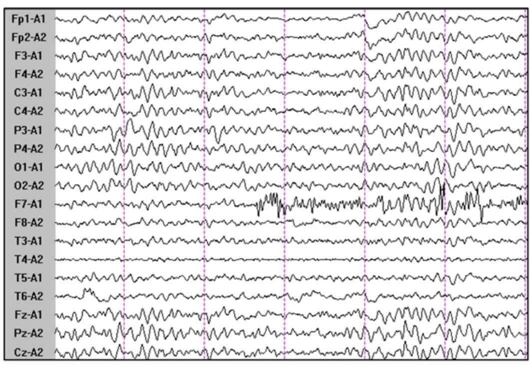

FIGURE 4. Recorded EEG signal.

Each session of EEG recording has 5-minute duration, sampled at 200 samples per second. Fig. 4. shows EEG recording of a 38-year female patient with ischemic stroke. The data is preprocessed in MATLAB. The EEG machine, named "Contec KT88-2400" when interfaced with a computer, generated ".eeg" file of the data which cannot be directly imported to MATLAB. Therefore, the data was imported using EEGLAB tool [38]. After the data was imported to the MATLAB using EEGLAB, it was exported in ".csv" format.

B. PRE-PROCESSING AND SIGNAL DE-NOISING

The raw EEG signal is subjected to pre-processing in order to remove the noise and decompose the signal into its sub-bands. Since EEG is a non-stationary signal, therefore traditional Fourier analysis of the EEG signal is not adequate for its time-frequency analysis. The Wavelet Transform is a more appropriate technique in this regard, which is a powerful mathematical tool for the analysis of any non-stationary signal in both times as well as frequency domain simultaneously. Wavelet transform uses a single function to represent the original signal with a fixed set of wavelets. The function that is used to derive all these wavelets is called mother wavelet. The wavelet transform is classified into continuous and discrete wavelet transforms. Continuous Wavelet Transform (CWT) projects a finite energy signal into a set of continuous frequency bands. Using CWT, a signal can be represented at every frequency in its spectrum. All of its resulting frequency components can be integrated to regenerate the original signal. However, this process is not computationally possible. A practical approach is to discretize the frequency band. Discrete wavelet transforms (DWT) uses discrete-time filters that are called "wavelet and scaling coefficients" in wavelets nomenclature.

There are several types of functions that are used as mother-wavelets such as Haar, Daubechies, Coiflet, Symlet, Bioorthogonal, Gabor and Symlet [39]. Symlet is the most suitable mother-wavelet used to decompose EEG signals [40].

EEG signals of Ischemic Stroke were subjected to 5 level wavelet decomposition using symlet wavelet. Original Signal was reconstructed using wavelet coefficients of each level. Reconstructed sub bands are depicted in Fig. 5. The highest sub-band (f>60Hz) was rejected in order to de-noise the EEG signal.

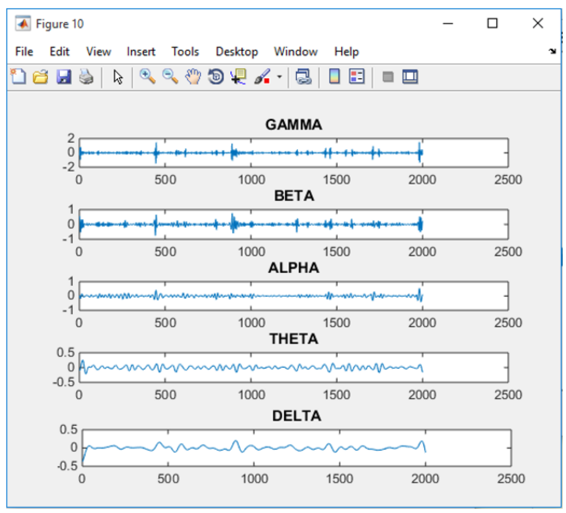

FIGURE 5. Reconstructed sub-bands of EEG signal using wavelet transform.

C. FEATURE EXTRACTION

EEG data from the individual channel was divided into epochs of 10 seconds. Thus, the signal from the duration of 5 minutes contains 30 epochs. There were three different features extracted from every epoch. The features include Delta Power, Relative Local Alpha to Delta Ratio (RLADR) and Local Delta Brain Symmetry Index (LDBSI). In the following sections, we will discuss these features in detail.

1) RELATIVE DELTA POWER (RDP)

Specific EEG bands are associated with certain functions of the brain. Alpha frequencies are generated by the cells of layer IV and layer V, whereas the slower frequencies such as delta and theta are generated by the thalamus, layer II and layer VI of cortex [41]. Neurons in layer VI (also called Pyramidal Neurons) are more sensitive to the low supply of oxygen. Therefore, the pyramidal neurons are the most affected cells in due to ischemic stroke [42]. When the blood supply is disturbed, the power slower frequency band (i.e. Delta) gradually increases. This is the most critical condition of stroke as the cells are unable to maintain the transmembrane gradient and eventually they die [43]. Ischemic stroke affects some part of the brain (one hemisphere) and the changes in EEG appear only in the channels of that hemisphere. Therefore, the difference in regional power of delta wave has been calculated and it is referred as Relative Delta Power (RDP). For a pair channel i (with i = 1, 2, 3,. . . .N), RDP can be expressed in equation 1 [36].

$$RDP_i = \left| \frac{LDP_i - RDP_i}{LDP_i + RDP_i} \right| \tag{1}$$

2) RELATIVE LOCAL ALPHA TO DELTA RATIO (RLADR)

Increase in the Delta wave power starts appearing when the blood flow to the affected part of the brain is reduced to 36% of the normal blood supply. However, at the very initial phase of Ischemia, when the blood supply is 70% of the normal range, faster frequencies begin to fade. Hence, when the blood supply is significantly reduced, the ratio of Alpha power to Delta power approaches zero. RLADR is the difference between the ratio of Alpha power to Delta Power of every pair of channel i (with i = 1, 2, 3, . . ., N) from both brain hemispheres. We can mathematically define RLADR as expressed in equation 2.

$$RLADR_i = \left| \frac{LAD_i - RAD_i}{LAD_i + RAD_i} \right| \tag{2}$$

The random variables LAD and RAD are the Alpha-Delta ratio of left and right hemisphere respectively, averaged over the epoch. Alpha and Delta waves are obtained from RAW EEG through the wavelet decomposition and reconstruction. Stroke introduces abnormalities in the Alpha and Delta waves. Attenuation of alpha and increase in delta are two major abnormalities. Therefore, the variable representing the ratio of Alpha and Delta (LAD and RAD) is used for clinical decisions of Ischemic Stroke [44].

3) LOCAL BRAIN SYMMETRY INDEX (LBSI)

Brain Symmetry Index (BSI) is one of the most recently developed techniques used to monitor the possible occurrence of brain ischemia during brain surgery [19]. BSI is a single value index that ranges from 0 to 1, where 0 represents normal brain and 1 represents the affected brain.

BSI is a measure of the difference between Power Spectral Density (PSD) of all channels of the left hemisphere and that of the right hemisphere. The hemispheric PSD is calculated for all bands of EEG for all channels. However, the change in delta wave power has the strongest correlation with ischemic stroke. Based on this claim, we have calculated BSI from the delta frequency band only for every pair of electrodes. Thus, instead of a single value index, we have one value for each pair of channels from the left and right hemisphere. LBSI is mathematically expressed in equation 3 [45].

$$LBSI_i = \left| \frac{LPSD_i - RPSD_i}{LPSD_i + RPSD_i} \right| \tag{3}$$

4) ALGORITHM OF SIGNAL PRE-PROCESSING AND FEATURE EXTRACTION

The algorithm of Wavelet Decomposition and Feature Extraction is a loop that will repeat for every epoch. Features extracted in each loop will then be subjected to classification. Steps of the algorithm are as follows:

STEP-1: Decompose signals into epochs

STEP-2: Take ith epoch from a pair of the channel (channel A and Channel B) for Wavelet Decomposition. Start with i=1.

STEP-3: Apply wavedec function using Symlet9 wavelet at a level to get wavelet decomposition vectors

STEP-4: Extract the detail coefficients and the approximate coefficient from the wavelet decomposition vectors at level 5.

STEP-5: Reconstruct signals from each coefficient vectors obtained in step 4.

STEP -6: Calculate the power of reconstructed delta wave for Channels A and B

STEP-7: Calculate the Relative Delta Power using equation 1

STEP-8: Calculate Alpha power from the reconstructed alpha wave.

STEP-9: Calculate RLADR from equation 2 using power ratio of Alpha and Delta wave

STEP-10: Apply Fast Fourier Transform (FFT) on reconstructed Delta Wave.

STEP-11: Calculate Power Spectral Density from the result of step-10.

STEP-12: Use equation 3 to calculate LBSI of A and B channel pair.

STEP-13: Repeat Step-2 after incrementing the value of i.

5) CLASSIFICATION OF BRAIN WAVES

Several classifiers have been tried in the research area of BCI. A comparison of some most commonly used classifiers is given in Table 2. Since the stroke detection is a two-class problem (i.e. either a person is affected or normal), Support Vector Machine (SVM) is the most feasible classifier in this case.

TABLE 2. Comparison of classifiers commonly used in BCI.

	Linearity	Generative / Discriminative	Dynamic / Static	Stability
SVM	Linear	Discriminant	Static	Stable
MLP	Non-Linear	Discriminant	Static	Unstable
k-NN	Non-Linear	Discriminant	Static	Unstable
HMM	Non-Linear	Generative	Dynamic	Unstable

6) SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine is a linear binary classifier. SVM uses hyperplanes to differentiate the data belonging to two different classes. For a particular training data, each test feature is marked for its relation to one class or other. The class of a feature is identified by analyzing whether the feature belongs to one particular side of the hyperplane or the other [46], [47]. Although Linear Discriminant Analysis also performs data separation based on hyperplane, the hyperplane selection in SVM takes into account the maximization of margin as shown in Fig. 6. SVM is found to be very successful in numerous BCI applications [48]–[50].

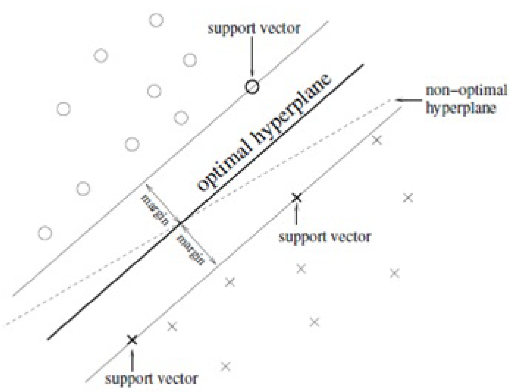

FIGURE 6. Support vector machine hyperplane.

IV. IMPLEMENTATION

The purpose of the proposed Cyber Physical System is to enable real-time remote monitoring of the patient, in order to detect the occurrence of stroke. The CPS was implemented on Android Device. The device was interfaced with wireless EEG headband device. A variety of Bluetooth enabled EEG devices are now commonly available in the market. The device used for the implementation of this work is MUSE Headband (shown in Fig. 7.). MUSE Headband is a

FIGURE 7. MUSE headband.

chargeable device that has 5 electrodes namely AFz, Fp1, Fp2, Tp9, and Tp10.

An Android application was developed to interface the MUSE headband with a mobile device. MUSE headband records the EEG and transmits to the mobile device. First two phases of the prognosis algorithm were implemented on the mobile device. The mobile device, after receiving the EEG signal of one Epoch, performs pre-processing and feature extraction. After every epoch, the features are transmitted to the cloud for classification purpose, and the EEG signal itself is discarded.

A. DATA ACQUISITION

The proposed CPS consists of three components (i.e. wearable headband, mobile device, and cloud). The interaction among the individual components should be based on the reliable communication protocols in order to abstain from the data losses. Interaction of the proposed CPS is depicted in Fig. 8. The communication between the wearable EEG device (i.e. MUSE Headband) and patient's Android device is made via Bluetooth (IEEE 802.14 protocol). Whereas, on the server side, WLAN (IEEE 802.11) is used for communication. Most of the real-time applications are implemented using User Datagram Protocol (UDP) because of its advantage of having peer-to-peer communication. However, UDP is more prone to packet losses in case of traffic congestion in the network. Loss of packets can lead to miss-detection of the stroke. Since CPS for detection of stroke is a critical application and it cannot afford packet losses, the protocol for communication between mobile device and server should be more reliable. TCP protocol is, therefore, the only choice for the proposed CPS system. TCP is most widely

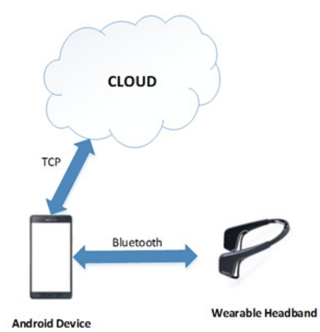

FIGURE 8. Communication architecture of the proposed CPS.

used for the data sensitive applications such as File Transfer Protocol (FTP).

B. DATASET

This sub-section, discusses the details of the dataset used for training and testing the proposed algorithm. EEG dataset of 15 ischemic stroke patients and 15 normal people were collected. An equal number of patients and normal people are analyzed; hence the dataset is balanced. EEG signals of 5 minutes were recorded with a sampling rate of 200 samples/sec. The machine was set to calibrate itself for one minute. Hence the useful EEG signal contains 4 minutes' recording. The total recorded samples per person are 4800. EEG data is divided into equal epochs of 10 seconds. One feature vector per epoch was extracted from EEG of electrode pairs.

Out of 30 subjects, a dataset of 20 subjects was used as training set to train the classifier. Rest of data was used to test the classifier.

C. ENERGY EFFICIENCY

The purpose of implementing first two phases on the mobile device is to ensure lesser consumption of mobile energy at the cost of computations. Computation consumes less power than the transmission. A raw EEG signal from 4 electrodes consists of 800 samples/sec. A total number of samples in one epoch of 10 seconds is 8000. If each sample is stored using short data type, the total amount of data to be transmitted per epoch will be 16KB. A standard Android Device (i.e. Google Nexus) consumes 2.08 joules per epoch to transmit the EEG data of 4 electrodes. On the other hand, if pre-processing and feature extraction are performed locally on the device, the mobile device will have to transmit the features instead of whole EEG signals. The proposed system uses three features (i.e. RDP, LBSI, and RLADR); there is one value of every feature associated with every pair of electrode. Therefore, for two pairs of electrodes of MUSE headband, a single feature consists of 6 values. If the short data type is used to store the features, the amount of data to be transmitted per epoch is reduced to 12Bytes. The energy required to transmit 12 Bytes over the WLAN is 0.00156 joules per epoch. The energy consumption is reduced by 99.925%, which is quite a significant amount.

V. RESULTS

The proposed system classifies the data based on three features. Every feature presents an index to measure the difference between EEG of the left hemisphere and right hemisphere. Hence, the value of every feature ranges between 0 and 1. This creates uniformity among the features. The following sub-sections analyze the difference between features of the normal person and stroke patients.

A. RESULTS OF RELATIVE DELTA POWER (RDP)

Relative Delta Power (RDP) of a normal person and a stroke affected person is plotted in the graph shown in Fig. 9. The plotted RDP is extracted from EEG recording of AF7 and AF8 electrode pairs. As can be observed from the plot, that the RDP of a normal person is relatively very low as compared to that of a stroke affected person. Average RDP of a normal person is observed to be 0.017, whereas the average RDP of a stroke affected person is 0.409. Fig. 10. depicts the RDP from TP9 and TP10 electrode pairs.

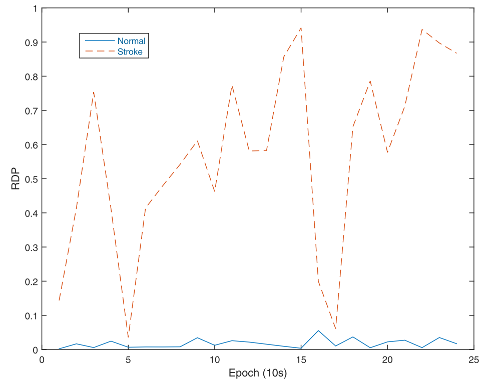

FIGURE 9. Relative delta power (RDP) of a normal and Stroke affected person captured from AF7 and AF8 channels.

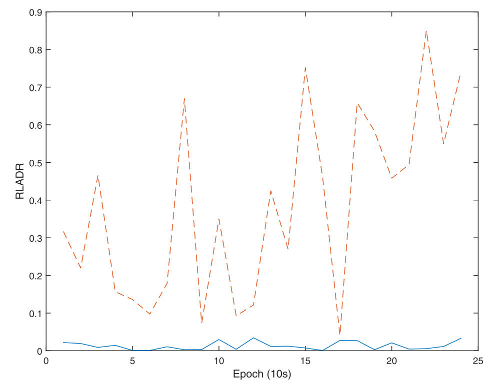

FIGURE 10. Relative delta power (RDP) of a normal and Stroke affected person captured from TP9 and TP10 channels.

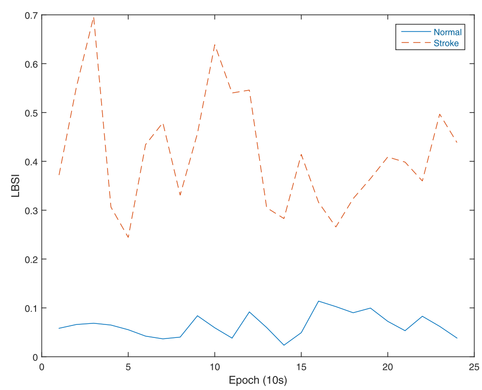

FIGURE 11. Local brain symmetry index (LBSI) of a normal and Stroke affected person captured from AF8 and AF9 channels.

B. RESULTS OF LOCAL BRAIN SYMMETRY INDEX (LBSI)

LBSI's of AF8-AF9 and TP9-TP10 electrode pairs are shown in Fig. 11. and Fig. 12. respectively. It can be be observed from the graph, that the Power Spectral Density (PSD) of

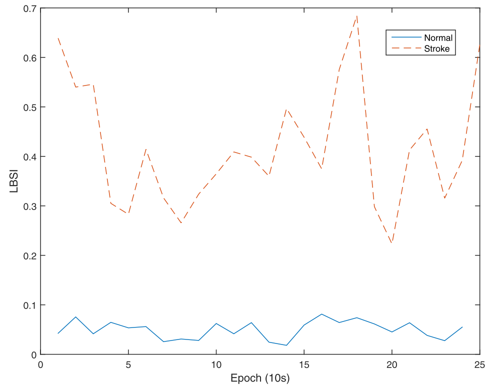

FIGURE 12. Local brain symmetry index (LBSI) of a normal and Stroke affected person captured from TP9 and TP10 channels.

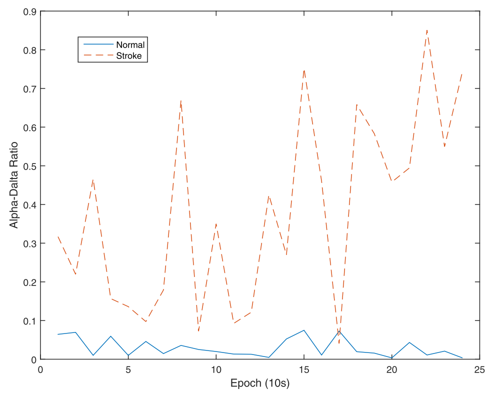

FIGURE 13. Relative local alpha to delta ratio of a normal and Stroke affected person captured from AF8 and AF9 channels.

delta wave of a stroke affected person is less symmetric than that of a normal person. Average LBSI of a normal person is observed to be 0.0691 and that of a stroke affected person is 0.3714.

C. RESULTS OF RELATIVE LOCAL ALPHA TO DELTA RATIO (RLADR)

Fig. 13. and Fig. 14. depicts the RLADR of a normal and stroke affected person respectively. A similar pattern is also observed in these plots. The RLADR of a normal person follows a lower profile than that of an affected person. Average RLADR of a stroke affected person is 0.3817. Whereas, the average RLADR of a normal person of 0.0717.

D. CLASSIFICATION OF RESULTS

Classification of the extracted features, was performed using WEKA (Waikato Environment for Knowledge Analysis) [51]. It is a java-based machine learning suite developed by University of Waikato, New Zealand. Results of SVM classification for each individual feature were analyzed separately. All features were then assembled in a single data to analyze the collective effect of all features on the results. Extracted features were formatted according to WEKA's supported data format (i.e. ".arff"). Training set used for training the SVM classifier consists of features extracted

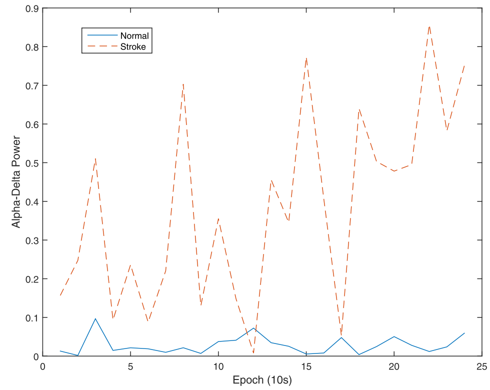

FIGURE 14. Relative local alpha to delta ratio of a normal and Stroke affected person captured from TP9 and TP10 channels.

from EEG of 10 normal and 10 strokes affected subjects. Test data contained features of 5 normal people and 5 stroke affected people. Since the duration of EEG recording of every subject is of 5 minutes, therefore, each recording contains 30 epochs. Each epoch is of 10 seconds. First 60 seconds are spared for machine calibration. Hence, 24 epochs are useful for feature extraction. From every epoch, one feature vector is extracted. In total, 240 feature vectors are extracted from data of 10 people. Table 3, shows the results of classification.

TABLE 3. Results of SVM classifier using LBSI, RDP and RLADR features.

	LBSI	LBSI, RDP	LBSI, RDP, and RLADR
TOTAL INSTANCES		240	
Correctly Classified	221	229	238
Incorrectly Classified	19	11	2
Precision	100%	100%	100%
Recall	84.2%	90.8%	99.16%

As can be seen from the table, that in the case when only LBSI is used for the classification, 19 instances are incorrectly classified. In this case, the precision is 100%, however, recall is 84.2%. After the RDP feature is added, an increase in the performance is observed. The correctly identified instances are increased to 229 and the recall is improved by 6.6%. Finally, with the addition of the third feature; RLADR, the performance is significantly increased. The correctly identified instances reaches to 238. The recall is enhanced up to 99.16%.

Hence, it can be concluded from the observations presented in Table 3, that the recall or sensitivity of the classifier is improved when more features of stroke are included. Table 4 compares the results of the proposed system with the state-of-art stroke identification mechanisms.

The precision of the proposed system is same as all other classifiers presented in the literature, known to the author. However, the recall of the proposed system is better than those of K-NN based and ANN based systems.

TABLE 4. Comparison of proposed system with K-NN based and ANN based classifier presented in literature.

	Precision	Recall
BSII Based System	91.7%	90.3%
K-NN Classifier Based System	100%	95%
ANN Based System	100%	98.8%
Proposed System	100%	99.16%

VI. CONCLUSION

Ischemic Stroke (IS) is a non-communicable disease that can lead to patient's mortality or disability, if it is not treated within 3 to 4 hours of its occurrence. Delay of patients' arrival at the hospital is the major cause is mortality due to IS. This article proposes a Cyber Physical System that can identify the occurrence of stroke using EEG recorded from patient's scalp using non-invasive EEG recording device. A prognosis algorithm is developed that pre-processes the EEG signal and extracts three features that are RDP, LBSI, and RLADR.

Relative Delta Power is the differential power of delta waves extracted from every electrode pair. Local Brain Symmetry Index is the difference of Power Spectral Density of Delta Wave and Relative Local Alpha to Delta Ratio is the difference of power ratio of Alpha Waves to the Delta Waves. Every feature is a unique value extracted from every electrode pair. In the next phase of Prognosis Algorithm, the extracted features are subjected to classification using Support Vector Machine (SVM). Features of 20 subjects were used for the training of SVM classifier and the test data contained 10 subjects including 5 Stroke patients and 5 normal people. Results were analyzed for three different cases. In the first case, only single feature (i.e. LBSI) was used for classification. In the second case, RDP feature was added and in the third case, all three features were included. It was observed that the precision was 100% in all cases; however, the recall or sensitivity in the first case was 84.2%. With the addition of the RDP feature, the recall was improved to 90.8%. Finally, when all features were included, the recall was observed to 99.16%.

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