IEEE Access
SPECIAL SECTION ON WIRELESS BODY AREA NETWORKS

Received April 13, 2019, accepted May 9, 2019, date of publication May 20, 2019, date of current version June 6, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2917718

Modeling Mental Stress Using a Deep Learning Framework

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ABSTRACT In this research proposal, the disparity in stress severity is modeled using a deep learning framework to determine mental stress. A wireless network sensor platform is used to monitor various physiological signals, such as heart rate variation, skin conductance, and breathing pattern irregularities that are activated by providing a challenging atmosphere inside a laboratory. A set of protocols is designed using a range of cognitive experiments that engage participants in a series of mental activities with various levels of challenges. The participant feels stress that varies in severity when undergoing these challenges. To relax the mind and body from stress, a deep breathing technique is used that is performed before and after each cognitive activity. Apart from the traditional physiological signals, cerebral features are also extracted from the neural signals. To identify the stressed activities and their severity, a convolutional neural network (CNN) framework is employed for training and validating the input datasets. It is found that the neural signals significantly improve the efficiency of the proposed classification model in computing mental stress. The study also supports the idea that the deep learning framework results in an improved estimate to determine mental stress.

INDEX TERMS Mental stress, cognitive experiments, deep learning, convolution neural networks.

I. INTRODUCTION

It has been established that external forces play a key role in causing the human body to respond. The response of the body to these external forces is called stress [1], [2]. Various physiological and psychological processes are triggered in stressful conditions. The wear and tear on the body that occurs as a person ages increase considerably with stress. Chronic stress weakens the body's defense mechanisms and decreases the strength of immune and cardiovascular systems in a human body. The immune system of the body becomes weaker, and a stressed person is potentially less resistant to infections and chronic diseases such as hypertension, asthma or diabetics [3].

In a stressful situation, the body's hormonal system reacts to stressors, and various physical and psychological changes occur [4]. In times of stress, the defense system of the body releases cortisol to activate muscles and joints. To determine the change in hormone levels, lengthy and invasive laboratory experiments are needed that are not very comfortable for a person. Various physiological variables that are associated with these hormones can be measured in an easy and comfortable environment [5]. For determination of stress, noninvasive measures including variation in heart rate, changes in respiration patterns or skin conductance are more convenient and accurate than physical marks that include facial expressions, speech or vocal changes and variations in gesture patterns [6].

Stress is caused by external environmental pressures that exceed the tolerant capacity of a person [7]. Feelings of depression or anxiety are the basic cause of stress. Chronic stress produces permanent changes in the physiological systems of a person, and long term diseases are developed such as asthma, diabetes and hypertension. In normal circumstances, the autonomic nervous system controls hormones such as catecholamine or cortisol that maintain the immune system and cardiovascular activities of a human body [8]. Chronic stress deregulates the activation of hormones, which results in an increased risk of psychiatric and physical problems. To measure and monitor the proper functioning of the hormonal system, invasive methods such as blood, urine and saliva sample tests are performed. Alternatively, there are

The associate editor coordinating the review of this manuscript and approving it for publication was Rajeeb Dey.

FIGURE 1. Sensors for skin conductance and respiration along with a holster unit.

a number of noninvasive methods that involve the measurement of biomedical signals which in turn are generated in response to stress. These biomedical signals contain heart rate pulsation, blood pressure, breathing patterns, skin conductance, pupil dilation, voice intonation and changes in body postures [9]. The physiological measures used to monitor stress in our research are based on the criterion that they should be convenient in terms of comfort and should be available such that their measurement will not hinder daily routine activities. These measures include heart rate variations, respiration patterns and changes in skin conductance. Other physiological parameters, such as pupil dilation or gesture recognition, whose measurement obstruct daily activities, are ignored [10], [11].

In this research project, a protocol is followed that contains a series of cognitive experiments which induce various levels of stress in the participants. Considering convenience and long term usage, a wearable sensor system is developed that does not hinder a person's daily routine jobs. It contains lithium batteries and can record physical and biomedical signals for up to a couple of days. In Figure 1, two sensors are displayed that record the physiological parameters and generate the biomedical data. The stress monitoring system should be able to monitor and record the negative effects of stress in a person and provide an objective assessment that should assist physicians. This objective assessment should describe stress in a person on a numeric format such as blood pressure or sugar level. A person is considered healthy when the range of measures is within prescribed limits, and he or she is considered to be cautioned and treated medically if the reading is outside the healthy range [12]. Blood pressure below 120/80 mmHg is classified in normal range while sugar level less than 140 mg/dL is considered to be normal. The protocol for cognitive experiments was approved by a team of physicians. There are two stages of experiments. In stage 1, traditional physiological signals from a heart rate monitor (HRM), electrodermal activity (EDA) and respiratory changes are recorded. In the second stage, cerebral and neural signals from an EEG of the participants are monitored. A comparison is drawn between the selected features and their patterns in both stages, and an analysis is also performed by combining all the features. It is found that accuracy metrics are enhanced when traditional features are combined with cerebral features.

The remainder of this paper is organized as follows. A discussion of the related work is given in the next section. Section III presents the methodology with a brief discussion of the proposed deep learning framework along with the explanation of heart rate variations and skin conductance. The experimental setup and formulation of the protocol sets are described in Section IV. The results and the relevant discussion is presented in Section V. Finally, the paper ends with concluding remarks about the proposed model and future directions for its extensions and potential applications.

II. LITERATURE REVIEW

There have been a number of studies on the importance of mental stress and its computations. The authors in [13] have proposed to compute mental stress from electroencephalogram (EEG) of stressed participants using the suggested machine learning framework. Using EEG spectrum, five features are extracted and after feature selection and employing three classifiers SVM, naïve Bayes and logistic regression, 94.6% classification accuracy is achieved. In [14], authors have designed a lightweight EEG sensor that can be used in our day to day routine. An algorithm for calibration of the sensor is proposed that can be tuned by users and the setting of electrodes can be adjusted. It is shown that chronic stress can be detected using EEG non-linear features. The discrete wavelength transform (DWT) and adaptive noise cancellation (ANC) based algorithm achieves 90% classification accuracy. In this research [15], Parkinson Disease (PD) is identified by processing radio signals that show variation when a normal person is walking in comparison to a person who has suffered from the disease. A leaky wave cable is used to capture the phase and amplitude features of the radio signals that are classified using the support vector machine (SVM). The classification results demonstrate an accuracy of 90% in closed monitored conditions. Similarly in [16], various sensors are used to incorporate facial and posture information in the proposed technique to compute mental stress.

The techniques in [17], [18] use heart rate variability (HRV) analysis to determine mental stress. The authors in [19] have identified wandering behavior of Dementia patients using omnidirectional antennas and a few wireless devices. The variations in the S band frequencies for phase and amplitude signals are recorded. The classification of the proposed system is performed with SVM that achieves 90% accuracy for the input three patterns. It is suggested that the early detection of dementia will assist in timely treatment of the patients and the bad effects of the disease can be limited. In [5], it is proposed that electrodermal activity (EDA) assists in differentiating stress from cognitive load in indoor office conditions. Stress levels of a person is computed from EDA signals by calculating its peak height and peak rate. An accuracy of 80% is achieved using cross validation and support vector machine (SVM).

The authors in [20] have proposed a breathing monitoring system that is non-intrusive and based on sensing technique for C-band wavelengths. The expansion of chest and its contraction are recorded using a microwave sensing platform. Applying a peak detection algorithm, normal breathing patterns are identified using variation in respiratory rates. Similarly in [21], the abnormality in gait and tremors in hand is detected using a framework containing a network interface card, omnidirectional antenna and a router that records the variance of amplitude and phase information with wireless channel interface. In [22], a wearable sensor system that uses EDA, ECG and EEG is designed to detect stress levels in a person. The aim of the proposed system was to correlate changes in salivary cortisol with changes in stress levels. The differentiation between steadiness and tremor conditions are identified in this research study [23]. Various features are extracted from time domain signals and their spatial proximities of wireless spectrum band that produced 90% accuracy. In [24], the authors have proposed that with fusion of near-infrared spectroscopy (NIRS) and physiological parameters, quality and accuracy for the assessment of mental stress would enhance significantly.

In a research study [25], heart rate monitors (HRMs) were used to detect changes in heartbeats that are proportional to mental stress. As stress increases, heart rate increases and their wavelength decreases. HRMs are used to capture heart rate signals, and their results have shown to be equally good in comparison to electrocardiogram (ECG). To extract features and determine accuracy results, pulse density modulation (PDM) technique is used for classification, and 83% accuracy is reported. The authors in [26] used heart rate variability with its spectral components. Ratios of the left and right sides of spectral frequency bands are used. The ratio increases with severity in stress. The experiments provided satisfactory results, but there is room for improvement in classification accuracy. In [3], the combination of heart rate (HR) and heart rate variability (HRV) features were used to determine stress. A small sample of 28 participants was used in the experiments. To induce stress, pictures were used for recognition in a short period of time. It was reported that short time HRV is proportional to mental stress, but thorough investigations are necessary to validate the results.

In [27], laboratory experiments were used to induce mental stress. The cognitive experiments contain memory tests for entering 6 digits on the screen. It was reported that the frequency ratio for the left and right bands increases in proportion to the severity of the stress levels. Blood pressure was also monitored, and it was noted that during stress, blood pressure remained high. A fuzzy clustering technique was used [28] to perform HRV analysis. Wavelet transform was used to extract features from heart rate variations. In experiments, air traffic control-based simulations were used. The stress was high, but the environment was not controlled, so the study has limited practical applications. In [29], stress levels were shown to be proportional to lower HR values, lower oxygen saturation in fingers and higher body temperatures. The test sample contains 25 female subjects and is classified as small for general acceptance of the results. The authors in [30] used deterministic fractals and a few basic properties of chaotic systems on the ECGs of the total 26 participants. A test system based on the ECG was designed that used fractal algorithms on HRV signal waveforms. In the various phases of the test such as resting, early stress and late stress, FD values was recorded that showed an increase in the magnitude levels from the resting to the stress phase. It has been reported that stress detection using fractal analysis can be useful for the assessment of stress severity. In [31], the authors used morphologic variability (MV) along with other measurable characteristics including various heart rate variability measures from ECG signals in both time and frequency domains. In [32], ultra short term HRV analysis was performed to compute mental stress. There were different HRV measures including mean of RR intervals (mRR), mean of heart rate (mHR), low frequency (LF), very low frequency (VLF), high frequency (HF) power spectrum and sympathovagal balance index (SVI) were used to detect stress levels.

The authors in [33] used a microwave reflectometric cardiopulmonary sensing instrument to detect mental stress levels. They developed two techniques that record HRV using dynamic motion signals on the body surface. Initially, a cross-correlation function was used, which found similarity between the recorded signal and a template signal that was designed by locally averaging the periodic components of the designed waveform. Second, the time variation of the heartbeat frequencies in the recorded HRV were reconstructed using an entropy method based on the maximum probability function. In [34], time-dependent variation analysis of HRV features was performed to compute chronic stress levels. In a given day, three different time periods were chosen to record HRV features. For classification, a logistic regression technique was used, which provided 63.2% accuracy levels. The authors in [35] used fuzzy clustering with machine learning classifiers for the assessment of mental stress. Heart rate variation analysis was performed online using continuous wavelet transform functions for smoothing the extracted signals. The experimental data were modeled using fuzzy clustering techniques. Various irregularities and uncertainties in the collected data were removed using fuzzy logic and regression techniques.

III. METHODOLOGY

Our proposed system contains a stress monitoring cap with a couple of embedded electrodes. There is an abdominal strap for the holster unit that contains three major components, a sensor hub, a data processing unit and a battery. For data storage, a 2GB mini flash card is used. The motherboard is made by Vertex Pro and can process at a 400 MHz processing speed. A STMicroelectronics sensor hub using a 3D accelerometer is integrated with a GPS unit made by Lynx Technologies, Inc. Wireless receivers and transceivers are built into the sensor hub to communicate with the HRM. The 3000 milli-Ampere-Hours Li-Po battery is charged by the inbuilt charging module in the holster unit that can last up to thirteen hours. In the following sections, the deep learning framework and a brief description of physiological parameters are presented.

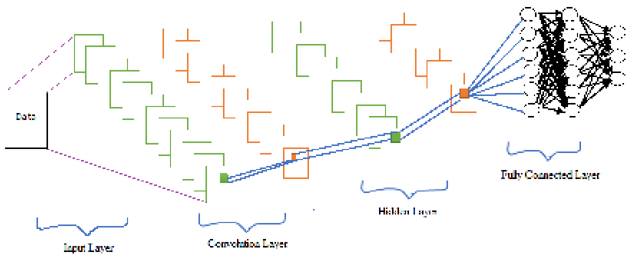

FIGURE 2. Convolutional neural network.

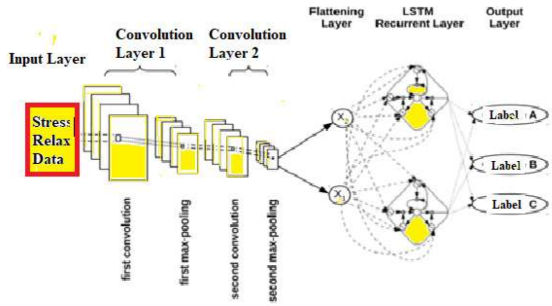

FIGURE 3. Recurrent neural network with LSTM.

A. DEEP LEARNING

There are several deep learning approaches that have been used in data mining and image processing applications. CNN (convolution neural network), ANN (artificial neural network) and RNN (recurrent neural network) are among the more popular techniques in a deep learning framework. Deep CNN is suitable for a large amount of nonlinear data that learns variations and shows high-level feature discrimination reflecting over the data [36]. In this research, deep CNN algorithms with triplets loss function have been employed. The convergence of the triplet loss function is difficult, and careful sampling is performed to achieve an efficient convergence. The characteristics of deep learning methods are such that they learn classification and discrimination features recursively. The new weights are computed in each subsequent iteration, and the process is repeated until self-adjustment of these weights are performed for a minimum threshold using large amounts of input data. In the convolutional neural network (CNN), the output data is convolved in a filtered network, and the output layer contains feature maps from the input. The entire convolution process is shown in Figure 2.

A fully connected network layer uses these feature maps and labels the input data accordingly. In CNNs or recurrent neural networks (RNN), three types of layers are generally involved: a convolution layer, a max pooling layer and fully connected layers. The basic advantage of CNN is that the model becomes independent of manually crafted features and its learning is based on start to end automated training using input images only. The weights in the convolution layer are shared among the pooling, and network layers and their adjustments are performed in repeated iterations that may iterate up to thousands or millions of times. In the subsampling layers, spatial resolutions of feature maps are reduced and lower dimensionality feature maps are produced. Subsequently, the dimensions of the input data are reduced, and the weights of the feature maps are tuned to produce accurate class scores for the given test data [37].

In deep CNN, many convolution and pooling layers are used to extract useful features from the input data. Training is performed on hyper-parameters of the designed kernels, and by iterating over the weights of forward and backward convolution layers, desired labels on the test data are achieved. Convolution layers form the fundamental block on a CNN framework. Kernel functions are designed using optimal window sizes. In CNN, feature extraction and classification are performed together in one block. Several convolution layers are followed by pooling layers to represent output data in a hierarchy of sequential weights [38]. Features from the convolution layers are passed to the predefined activation functions of sigmoid or hyperbolic tangent kernels that result in a nonlinear hyper-tuned neural networks. Feature vectors are proportional to the kernel size which is always less than the input data size. The function of the pooling layer is to reduce the dimensionality of the input data by decreasing the training time. A popular pooling technique is called max pooling, and layers are named accordingly. The max pooling layer chooses those convolution layers whose output labels are in accordance with the desired labels. A one-dimensional array is formed from the pooling layer and passed to the fully connected layers where the training cycle restarts using forward and backward propagations. The training is based on the gradient descent and dropout filter parameters that maintain the regularization of the training phase. In the iterative training process, certain neurons are dropped based on their low probability values, and in the next propagation, this process continues in the input and hidden layers of the neural network frame until the desired output label results are achieved. In Figure 3, experimental data is convolved in the recurrent neural network framework.

B. HEART RATE VARIATIONS

To monitor heart rate activity, ECG is considered to be the gold standard. For ECG, cumbersome wiring and electrodes are used which are not convenient for long term monitoring [39]. Heart rate activity can also be monitored using pulse oximetry, but it is prone to motion artifacts. A convenient method for recording heart rate activity is to use heart rate monitors (HRM) that capture variations in heart rate. An HRM consists of a chest strap that is worn such that the monitor is placed directly over the heart. A holster unit records the signals transmitted from a wireless sensor. In our experiments, a Polar Wearlink HRM from Polar Electro Inc. is used. Figure 1 shows a complete set of hardware devices that consists of respiratory and EDA sensors along with a holster unit that contains auxiliary devices.

In heart rate variations, respirations perform a significant part and must be monitored. To record respirations, a wide range of devices can be used. Respiratory inductive plethysmography (RIP) is used to record the changes in a magnetic field of encapsulated coils for detecting respiration effects. In impedance pneumography (IP), two electrodes are placed on the rib cage. They monitor impedance changes due to respiration and convert the changes to alternating current. Considering convenience in long term monitoring, both RIP and IP are potentially inappropriate as they are sensitive to motion artifacts and postural changes. We used a respiration sensor based on pressure signals made by Thought Technology Ltd. containing an SA9311 M sensor. It can be easily integrated into our chest strap and is not influenced by motion artifacts [40].

C. SKIN CONDUCTANCE

To monitor electrodermal activity (EDA) or skin conductance changes, a small electrical voltage is applied to the two electrodes that are placed on the adjacent fingers of a person's non-dominant hand. When a person is stressed, body glands produce sweat in the fingers and palm that results in an increase of conductance. To monitor EDA, palms of the hands are not convenient for long term use and using adjacent fingers is comfortable as one can freely use his/her hands. Two electrodes, made up of Gal, are placed on the central finger and its adjacent fingers of the non-dominant hand to measure variations in skin conductance. We used E243 electrodes that are made by Vivo Metric Systems Corp.

In EDA, SCR records the skin conductance at short time intervals whereas SCL represents the impedance of conductance for larger time periods [41]. The features of EDA are linearly proportional to stress levels as conductance increases with high stress and decreases in low stress. In contrast, HRV parameters vary inversely with the levels of stress. In the extracted components of EDA, SCL captures slowly changing offset, and SCR shows a continuous series of intermediate peaks.

The mean factor of the SCL signal is derived as follows,

$$\mu_{SL} = \frac{1}{N}\sum\nolimits_{i=1}^{N} R_{SL}(t-i)$$

In this equation, t is the time and μ_{SL} is the average or baseline EDA for the past N number of samples that is taken from the $\mathrm{R_{SL}}$ distribution.

The standard deviation factor is defined as follows,

$$\sigma = (\sum\nolimits_{i=1}^{N} R_{SL}(t-i))^{\frac{1}{2}}$$

In this equation, standard deviation is represented by σ_{SL} of the conductance signature signal that is denoted by $\mathrm{R_{SL}}$. Similarly, μ_{SR} and σ_{SR} are derived using transformation in residual SCR. We have used the SCL signature signal in our classification model as it linearly represents the levels of perspiration on a human palm and fingers.

In the EEG technique, cortical circuitry and cerebral signals are explored. There are many artifacts in the EEG signals such as eye blinking and muscle activities [42]. These artifacts distort the quality of neural signals. Generally, ICA is used to remove these artifacts from pure brain signals. Although minor data is lost in artifact suppression, the power spectrum of neural activity efficiently denotes the changes in the brain state. The data for EEG is acquired using the ECL electrodes with two electrodes placed according to the standard guidelines. The signals were filtered at a rate of 256 Hz using band-pass filters in the range of 4-400 Hz.

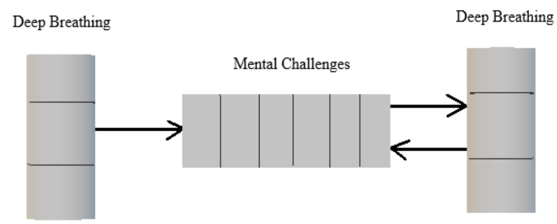

FIGURE 4. Cognitive experiments block diagram.

IV. EXPERIMENTS

Cognitive experiments were designed to induce mental stress in the participants. In our experiments, a total of 24 participants participated in the experiments in two stages. In stage 1, traditional signals were obtained using a wireless sensor platform from the heart, fingers and chest of the person. In stage 2, ECL electrodes from the head of a person were wirelessly connected to a sensor hub. Each subject was asked to provide written consent for his/her participation. A participant should be healthy and free from any physical or psychological disease, and therefore, a doctor examined the subject's physical fitness. All the mental challenges were explained before the experiments, and it was assured that the participants should not be pre-trained for the activities. A block diagram showing the cycle of the activities is presented in Figure 4. Before the experiments, a deep breathing exercise was performed as well as after each cognitive activity to relieve the effect of stress on the body.

The protocol for the experiments was designed to ensure that participants feel stress when they undergo these challenges. There were five mental challenges and between each challenge, the deep breathing exercise was performed. The experiments started with the deep breathing activity, and the devices were calibrated for each participant. The deep breathing technique activity lasted for 3 minutes in which a participant inhaled for 4 seconds and exhaled for 6 seconds. The first mental challenge was memory search or retrieval. It was followed by a deep breathing session. In the second mental challenge, a color word test was performed for five minutes. The participant had to answer with the right color when he was confounded with sounds, display or letters of the color. At the end of the challenge, a 3rd deep breathing session was performed. The next mental activity required tracing the mirror image of a sketch that lasted approximately 3 minutes. The fourth and fifth challenges were dual task and public speech. Finally, the last session of deep breathing was performed. Each participant was provided with a survey form and he/she had to rate each activity on a Likert scale of 1 to 7 where 1 represented a minimum difficulty challenge, and 7 was rated as the most stressful activity. A screenshot of a

TABLE 1. Selected features.

Signals	Features
HRM	mean_AVNN, med_pNN25, mean_RMSDD, h_HRV, l_HRV, med_HRV
RESP	Mean_RSP, med_RSP
EDA	mean_SCL, mean_SCR, med_SCL, med_SCR,
EEG	mean_BVP, mean_PTT, med_BVP, med_PTT

color word test (CWT) is shown in Figure 4. In CWT, fast and random questions are asked to judge the color on sound, typing or display of the color bar. The user becomes confused as the sound, word and display all are depicting with different colors, and the answer has to be provided in seconds. It was developed on the Android platform and causes the user to feel real stress while playing

In stage 1, the wireless sensor platform recorded various biomedical signals from the lower part of the body. In stage 2, neural signals were captured from the upper part of the body. In stage 1, 12 features were extracted, and four features were computed from the neural signals in stage 2. In stage 1, heart signals were processed by a peak detection algorithm at 500 MHz, and output signals were sampled at 4 Hz. A band-pass filter in the range of 0.04 to 0.4 Hz was used in heart rate monitor circuits to remove very low-frequency components (VLF). Using variations in heart rate, four features were extracted. AVNN is the first feature, which is a mean of the elapsed time between heartbeats. The other feature, pNN25 is used to identify the difference in the percentage power of the signal that is greater than 25 m seconds for adjacent beat intervals. The root mean square of successive difference (RMSDD) constitutes the 3rd feature whereas high-frequency power of HRV is the fourth extracted feature. The fifth and sixth features are low-frequency power density and the median value of heart rate variability. In respiration, mean_Resp represents a low-frequency respiratory power signal while the median of the power density is denoted by med_RSP. Extracted features from the lower body containing heart rate, respiration and EDA and cerebral parameters derived from the neural signals are presented in Table 1. There are two respiratory features that show chest compression in the time of stress. Altogether 12 features were extracted in stage 1 but four features were discarded due to redundancy.

In the second stage, the neural signals were analyzed to monitor the brain states of the brain when a person is stressed. Brain activity, if monitored, can assist in determining stress. There are some laboratory methods that are used to analyze brain signals such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG) and positron emission tomography (PET). The most common technique for analysis of brain signals is EEG as it contains a high temporal resolution. Also, it is less expensive than other methods. Neural activities in the brain trigger electrical signals. The brain signals can be recorded in the form of complex electrical waveforms using electrodes on the scalp. The charge on the electrodes is maintained at 20 to 100 microvolts and are similar to headphones; they are placed on both sides of the brain hemispheres. Various features such as frequency, amplitude, base length and shape of the scalp are used for the analysis of brain waveforms. In emotional situations, activities in the right hemisphere of the brain are more dominant then activities in the left hemisphere. Hence, for determining stress, it is the right hemisphere of the brain that needs to be explored for further analysis.

Analysis of the EEG waveforms was performed using amplitude and frequency of the brain signals. The mental state of a person is defined by Alfa (α) and Beta (β) waveforms that are used to represent consciousness [43]. The other state, or unconsciousness, is represented by Theta (θ) and Delta (δ) waves. When a person is stressed, Beta waves frequencies are more dominant, whereas Alfa waves show little variations. To analyze brain signals, Fourier transform and, band-pass filtering was used. Various features that determine identifiable patterns to show the presence of stress were extracted. Wavelet packets can also be used to filter high-frequency brain signals for extraction of features in the spatial domain while Fourier transform is used for features in the time domain. Mental stress is determined using these features as densities of Alpha and Beta power spectral bands. These ratios are quite significant because Alpha ratios denote the presence of stress whereas Beta ratios determine the severity of stress.

The ratios are defined as follows:

$$r_\alpha = \frac{\alpha R - \alpha L}{\alpha R + \alpha L}$$
$$r_\beta = \frac{\beta R - \beta L}{\beta R + \beta L}$$

In these equations, α_{L} and α_{R} are the lower filtered frequencies, whereas β_{L} and β_{R} are the higher frequencies in the left and right side of the brain, respectively. It is reported that low frequency alpha (α) waves, slower (lower frequency) and higher in amplitude, indicate a relaxed state while beta (β) waves, high frequency and low amplitude, represent a busy or concentrating mind which indicates a stressed situation if concentration of these waves is high. Theta waves are even greater in amplitude from alpha waves and lower in frequency and represent positive and relaxed state of mind. Delta brain waves are greatest in amplitude and have lowest frequency and represent a very relaxed mind condition such as a deep dreamless sleep. If no stress or relaxation is to be determined, then other measures including the integral summation of alpha and theta frequencies and the quotient of alpha, beta and theta sums are used. We extracted four features from these power spectral densities and used them in the classification model to test the accuracy of the system. In the second stage, these features were combined with the lower body features and a comparison was made to investigate the effect of neural features in enhancing the accuracy of the proposed model that determines mental stress [44].

V. RESULTS

In our proposed model, tuning was performed on a number of hyper-parameters used in the convolutional framework in our input data. There were 500 filters, the fitter window size was 5, the pooling strategy was softmax, the activation function was tangent hyperbolic with the dropout equal to 0.5 and the number of epochs was 30 with a unit stride length. The extracted data were divided into two sets, and 70% were used in the training while 30% were used for validation and testing. The test accuracy for labeling was almost 90%. This showed that the proposed model accurately tagged the test data and achieved reasonable performance.

The cognitive experiments followed a protocol such that the difficulty level increased in each activity, and the level of the stress increased gradually, which puts more stress on the participants. At the beginning and in between the activities, the relaxation technique based on deep breathing was performed to maintain the composure of the person. It has been reported that the self-esteem and the mental strength of a person is a guard against stress and makes him or her non-vulnerable against anxiety or stress. In our experiments, the activities were divided into two classes, stress class and relax or non-stress class. The experiments were performed in two stages. In stage 1, the lower body signals were recorded, and in stage 2, brain signals were monitored. For classification, in the first phase, only the lower body features were used. In the second phase, only cerebral features were employed in CNN for the classification. Finally, both lower body and cerebral features were combined, and their effect on the quality metrics was determined.

Quality metrics are presented in Table 2 and are also shown in Figure 5. Accuracy of the results discriminate subjects into two classes, with and without stress. Sensitivity, proportion of true positive subjects in the total group of subjects, show probability for the participants who are in the stress class. Specificity shows the probability of the subjects who do not have stress and are in the relaxed conditions. Positive predict value (PPV) represent proportion of subjects with stress in the total of subjects with stress while negative predict value (NPV) show proportion of subjects without stress in the relaxed class. In our study, PPV and NPV show induction of stress in the participants undergoing cognitive experiments. Higher values of PPV show effectiveness of the experiments in inducing stress among the subjects.

From Table 2, it is interpreted that the combined features resulted in an increase in the accuracy levels compared to the instances when features were used separately.

TABLE 2. Quality indices.

Quality Metrics	Lower body	Cerebral	Combined
Accuracy	84	87.5	90
Sensitivity	85.5	87.5	89
Specificity	81	84	86
PositivePredValue	82	85	87.5
NegativePredVaue	80	81.5	84.5

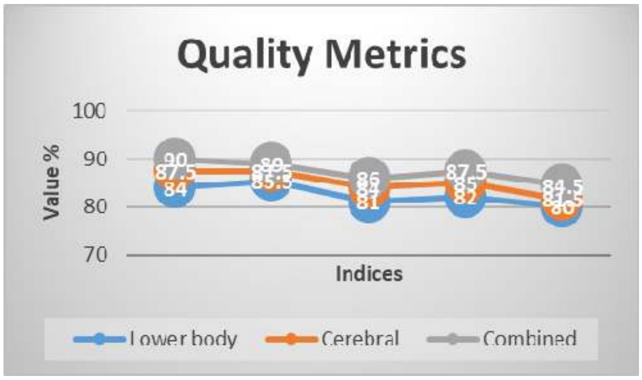

FIGURE 5. Quality indices for the selected features and their combination.

The stressful activities have to be differentiated from the relaxing techniques during the breathing sessions. As evident from Table 2, the accuracy was enhanced when features were combined. Other measures such as specificity and sensitivity also improved in the combined feature testing suggesting that only a few breathing sessions were reported as stressful. The reason for this was that some of the participants had difficulty during breathing in and out in a relaxed situation. In fact, the participants might have felt stressed during the breathing sessions. This results in their physiological signals depicted stress in a few breathing sessions. This phenomenon produced a negative effect, and a decrease in the quality of the metrics was reported. Using CNN with hidden layers, reasonable classification performance was achieved, which was enhanced further when the lower body features were combined with cerebral features. Although breathing while stressed lowered the quality metrics, the addition of neural parameters improved the accuracy and almost nullified the misclassified breathing patterns.

VI. CONCLUSIONS

We developed a wireless sensor model that records physiological and neural signals from the brain, heart, respiration and skin conductance of a human body. The participants underwent a series of cognitive challenges that induced mental stress varying in severity. Induced stress was computed from the extracted features that were determined using power spectral densities and logistic regression techniques that were employed on the physiological and the neural signals. The effect of inclusion of the brain signals in the traditional physiological parameters was determined in a detailed comparative analysis. Although computing stress with only the lower body parameters depended on a number of factors and it provided satisfactory quality levels, the addition of the cerebral parameters improved the accuracy with a significant margin. It was shown that under severe stress conditions, induced stress was proportional to changes in the brain signal patterns that could be monitored using the Laplace transform and the filtering algorithms.

Including cerebral parameters reduced the convenience of the wireless platform as a few electrodes were added in the system. They were connected with the head of the body through thin cords and terminated in the holster unit. To reduce the complexity and inconvenience, only two electrodes were attached that captured almost the same signal strength as captured by five or six electrodes. In stress, there were notable peaks in the brain waveforms that identified them clearly from the relaxed and the casual states. The deep learning strategy outperformed the other machine learning algorithms and the same was true in our case as well.

The protocol for our cognitive experiments was well-designed, but in the future, more challenging tasks on an Android platform may be added. The number of the current participants was medium, and in the future, more participants have to be engaged for the experiments. Also, it is suggested that real scenes of stress can be added in addition to the laboratory experiments. One such situation may be an examination session where our wearable wireless sensor platform can be worn by the students. In addition to that, a fire fighting situation can be monitored as fire-fighters undergo real-time stress. In the classification model, it is proposed that algorithms based on shallow learning may be used for a possible increase in classification accuracy. Finally, the design of the electrodes can be modified to enhance the portability of the system.

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