Public Health Initiative: Enhancing Stress Evaluation using EEG Data

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KEYWORDS

EEG (Electroencephalography), Stress Evaluation, Social Spider Advanced Bidirectional Long Short Term Memory (SS-ABiLSTM), Public health, Signal processing, Discrete Wavelet Transform (DWT).

ABSTRACT

Study proposes an innovative public health that uses EEG data processing to improve stress assessment. Stress is a widespread health issue that affects people in a variety of demographics. Stress evaluation techniques based on traditional self-reporting are biased and subjective. EEG records patterns of brain activity linked to stress reactions and offers an objective measurement. In this study, we proposed Social Spider Advanced Bidirectional Long ShortTerm Memory (SS-ABiLSTM), an innovative method for improving stress evaluation by integration of EEG data. Initially, EEG data is gathered, and then preprocessed the EEG data using min-max normalization to remove inaccurate records from a dataset. To extract features from the preprocessed data using the Discrete Wavelet Transform (DWT), this reliably extracts frequency-domain information from the data. The most discriminative characteristics for stress assessment to select feature using Recursive Feature Elimination (RFE). By combining these methods, stress assessment models that utilize EEG data have high accuracy. Utilizing the application of SS-ABiLSTM, that addresses stress prevention and management while also improving the ability to interpret EEG data in public health. The proposed methods are to evaluate F1-score (90.1%), precision (88.2%), recall (91.8%), and accuracy (98.97%). The accuracy of the proposed technique is superior to the existing techniques. Finally by using EEG data for stress evaluation in public health shows potential for more individualized care and better mental health results.

1. Introduction

Stress is a widespread problem in public health that affects both physical and mental health. Self-reports and other traditional evaluation techniques frequently lack reliability and impartiality [1]. The public health effort aims to enhance stress assessment through the development of user-friendly instruments for early identification and treatment of stress-related disorders [2]. The stress management in communities and workplaces by integrating screening and educational initiatives, promoting proactive stress identification and management, reducing healthcare strain, and highlighting mental health as a foundation for overall well-being [3]. Innovation technology is used progressively to improve stress assessment methods, such as electroencephalography (EGG) [4]. EEG data, a non-invasive technique, provides real-time insights into stress levels by assessing brain activity using scalp sensors, potentially identifying patterns and abnormalities linked to mental states [5]. The primary goal is to enhance the precision and efficacy of public health measures for stress reduction and public health support by including EEG data analysis into stress assessment [12]. Remaining section as follows, part 2 describes related work, part 3 describes methodology, part 4 describes result and part 5 describes conclusion.

Related work

Roy et al [13] explained to effectively identify psychological stress by applying automated extraction of features to transform multidimensional EEG data using convolution neural network (CNN) was suitable for therapy and the avoidance of physical and psychological issues [11]. Delmastro et al [7] investigated the use of wearable sensors and mobile health apps for stress monitoring during cognitive and motor rehabilitation in elderly people with mild cognitive impairment (MCI) [6]. The purpose of monitoring stress levels online was to estimate the stress level at the moment. The acquired outcome decision support system (DSS) would assist the healthcare provider in developing a customized treatment plan for elderly patients who are frail. Kamińska et al [8] explained EEG-based stress classification in virtual reality (VR) environments, building on methods using the Stroop test as a stressor and bilateral stimulation for relaxation [9]. The results were achieved while using Support Vector Machine (SVM) classifiers that corrected for each brain waves. Alhalaseh and Alasasfeh [14] automated EEG-based emotion identification model that extracts features using entropy and HFD and signals with the help of variational mode decomposition (VMD) the reactions to various feelings produce human emotions, which in turn influence brain signals and Naïve Bayes (NB), classification achieved accuracy was high [15].

2. Methodology

In this section, initially EEG data is gathered and data preprocessing is employed using min max normalization, and DWT is used to extract the features then select important features using RFE, the proposed SS-ABiLSTM is executed and explained in detail. Figure 1 illustrates the framework of the methodology.

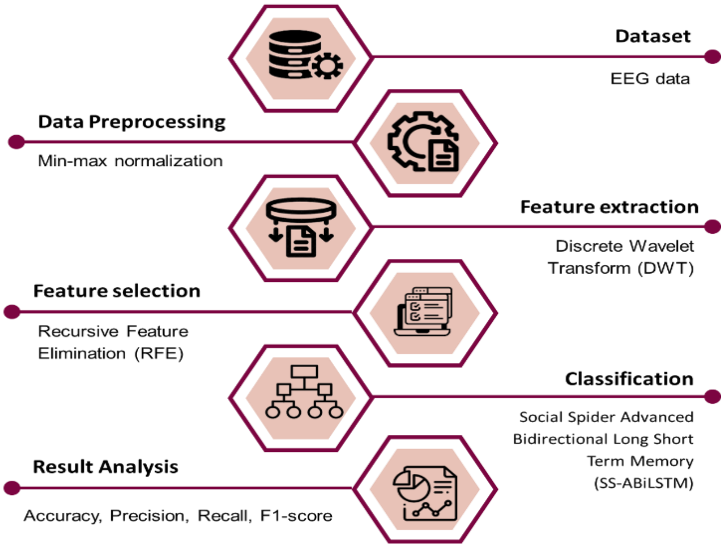

Figure 1 Framework of proposed methodology

Dataset

EEG Dataset collected from kaggle website (https://www.kaggle.com/datasets/samnikolas/eeg-dataset) dataset contains [10]. The assessments, physiological information, and facial recordings of subjects are part of an investigation where 32 volunteers watched a 40-selection of the previously stated music videos. Every participant assigned the videos an A rating, and physiological and EEG signals were also captured.

Data preprocessing using Min max normalization

After collecting the dataset pre-processing is handling missing values, eliminating duplication and pre-processing assists in clearing up the data. EEG data is normalized using Min-Max scaling for the public safety determination, which aims to improve stress measurement. By scaling data to a predetermined range, this technique ensures that EEG signals are comparable and assists with reliable stress evaluation by providing normalized values using equation (1).

$$Y_m^j \frac{y - y_{min}}{y_{max} - y_{min}} \tag{1}$$

Where y_{min} and y_{max} are minimum and maximum, normalization scales EEG data range 0 to 1, improving feature comparability and minimizing bias result from feature scales and inaccurate records from a dataset.

Feature extraction using DWT

After pre-processing, DWT feature extraction provides an in-depth analysis of brain activity dynamics and improves the assessment of stress using EEG data by capturing frequency variations across various scales. For EEG signal processing to function as well as be feasible, the feature-extraction method is essential. To deal with limited number of values that characterize the properties of the EEG signal are separated into extended time-series. The results of this calculation are combined into a vector known as the feature vector, and these are referred to as features. Where S is the wavelet space and z and w are the scaling and shifting parameters, respectively. The wavelet transform can be seen in the following equation (2).

$$\psi(s) = \frac{1}{\sqrt{2}}\psi\left(\frac{s-z}{w}\right) \dots . w, z \in T, w > 0 \qquad (2)$$

Consequently, wavelet transformations use a single function to break down signals into many functions to assess the signal's properties in both the time and frequency domains in equation (3).

$$E(w,z) = \frac{1}{\sqrt{w}}\int_t \psi\left(\frac{s-z}{w}\right) cs \qquad (3)$$

DWT was utilized as a method based on the capacity to produce a wavelet representation with high accuracy, the first-level decomposition by utilizing low and high-pass filters. DWT decomposition is defined by the following equation (4).

$$\left(\frac{s-z}{w}\right) = \sum_{l=-\infty}^{l=+\infty} D_{m,l}\emptyset(2^{-m}s - l) + \sum_{l=-\infty}^{l=+\infty}\sum_{l=-\infty}^{l=+\infty} 2^{-i/2} c_{i,l}\psi\left(2^{-i_{s-l}}\right)$$
(4)

EEG signals and feature extraction using DWT provide strength for stress calculation, capturing frequency-specific details crucial for EEG analysis and classification tasks.

Feature selection using RFE

After extracting the data, feature selection has described its minimization of model over-fitting. RFE feature selection maximizes stress assessment from EEG data, improving accuracy by detecting important EEG signals while lowering noise, which is essential for accurate stress assessment. Feature j is the context of EEG data; mj_i is measureable value that represents the significance in each node in equation (5).

$$ej_j = \frac{\sum_{i:node\ i\ splits\ on\ feature\ j} mj_i}{\sum_{l\epsilon\ all\ nodes} mj_i} \qquad (5)$$

Equation (6) has determined the significance of each characteristic on the selection graph of EEG ratio function.

$$norm\ ej_j = \frac{ej_j}{\sum_{i\epsilon\ all\ features} ej_i} \qquad (6)$$

$norm\ ej_{ji}$, is normalization process of ej_j scale data into a common range, QEnumber of signal is often to safeguard comparability between different measures in equation (7).

$$QE\ ej_j = \frac{\sum_{i:all\ trees} norm\ ej_{ji}}{S} \qquad (7)$$

EEG data by improving the detection of pertinent features, which is essential to accurate evaluation and effective diagnosis in EEG records.

Stress evaluation framework

We evaluate the stress with this innovative framework SS-ABiLSTM, bidirectional processing to efficiently model connections, which is to enhance predictive endurance for applications including categorization and sequencing predicting.

Advanced bidirectional long short term memory (ABiLSTM)

ABiLSTM classifies brain states from sequential patterns in EEG data, improving the understanding of brain diseases like epilepsy and sleep disorders as well as cognitive functions. The cellular state model has an industrial belt-like appearance. A minimum linear connection occurs along the conveyor belt. Its information flow is controlled by an internal mechanism called a "gate" that is introduced by ABiLSTM. Such connection structures have the ability to recognize which data should be destroyed and which is required to remain in order. Three gates allow the ABiLSTM to regulate and safeguard cellular states in equations (8) to (11). e_s denotes bias term for the gate, j_s represents the management of information flow over the network, guaranteeing the safeguarding of important information, $\widetilde{D}_s$ is denotes based on the prior hidden state and current input, ? presents a possible update to the hidden state. D_s represents EEG scale timestamp s.

$$e_s = \sigma(\omega_e \times [g_{s-1}, w_s] + a_e) \quad (8)$$

$$j_s = \sigma\left(\omega_j \times [g_{s-1}, w_s] + a_j\right) \quad (9)$$

$$\widetilde{D}_s = tanh(\omega_d \times [g_{s-1}, w_s] + a_d) \quad (10)$$

$$D_s = e_s \times D_{s-1} + j_s \times \widetilde{D}_s \quad (11)$$

The number of prior storage cell states that are currently going through the ABiLSTM unit is determined by the remembered gate. The input and output gates modify the storage unit's state using data from input and hidden states, enabling ABiLSTM to learn time correlations in long-term sequences. After classifying stress, the optimization was explained.

Social spider (SS)

EEG data is used to process brain signals, minimize noise, and improve signal quality and cognitive processes. Social spider features such as merging, food scavenging, and communication many social spiders are categorized as male or female, with females making approximately 60–90% of the whole population. To obtain details about their target, such groups create a web, or search domain. To identify the best and worst outcomes, as shown in equation (12), this approach entails employing equations. This approach supports improved stress assessment with EEG data.

$$R_i b_{nj} = l_i z^{-c_{ij}^2}, g_j = \left|\left|w_i - z_j\right|\right|, y_j = \frac{j_j - worst_n}{best_v - worst_n} \quad (12)$$

The minimum and maximum stress levels are communicated by the vibrations a spider makes as it moves between places and the stress level analysis is improved because of the EEG data.

$$worst_w = \min_{l=1,2,\ldots,M} E\left(v_j\right) + best_v = \max_{k=1,\ldots,n} (w_i) \quad (13)$$

Where, $\left(v_j\right)$ stands for spider j'size, vibration among $i$and j attentional function and fitness functions value was respectively in equation (13).

SS-ABiLSTM is a method for public health stress prevention and management while also improving the interpretability of EEG signals. Enabling more detailed in evolution of seizures and accurate stress evaluation in an assortment of public environments.

3. Results and discussion

This section describes the efficiency of the suggested SS-ABiLSTM approach along with how we evaluated it using Python software. Parameters including f1-score, precision, accuracy, recall and the existing methods are decision tree (DT) [11], random forest (RF) [11], k-nearest neighbours (KNN) [11] and extreme gradient boosting XGBoost [11]. Table 1 shows the numerical outcomes of the parameters.

Table 1 Numerical outcome of accuracy, recall, f1 score, precision

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT [11]	86.82	83.96	81.63	85.28
RF [11]	86.42	85.32	84.44	82.31
KNN [11]	86.45	83.39	85.53	83.37
XGBoost [11]	96.96	85.56	86.23	86.21
SS-ABiLSTM [Proposed]	**98.97**	**88.2**	**91.8**	**90.1**

Accuracy: EEG data for stress assessment improves the precision and dependability of stress measurement, increasing accuracy in public health evaluations. The comparison of accuracy among the existing approaches and proposed method is displayed in Figure 2. When compared to other existing approaches, the proposed SS-ABiLSTM approach achieved 98.97%, DT obtained 86.82%, RF obtained 86.42%, KNN obtained 86.45%, and XGBoost obtained 96.96 %. It demonstrates the greater efficiency in stress classification using SS- ABiLSTM.

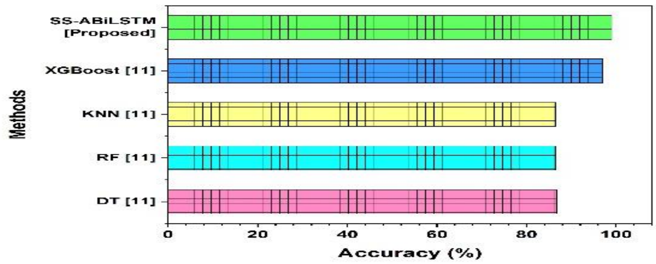

Figure 2 Comparison of accuracy

Precision: Finding the total number of precise positive forecasts from the number of positive predictions is the target of precision calculation. The comparison of precision among the existing approaches and proposed method is displayed in Figure 3. When compared to other existing approaches, the proposed SS-ABiLSTM approach achieved 88.2% with existing methods are DT (83.96%), RF (85.32%) KNN (83.39%), XGBoost (85.56%). The results illustrate how SS-ABiLSTM can classify stress with increased efficiency.

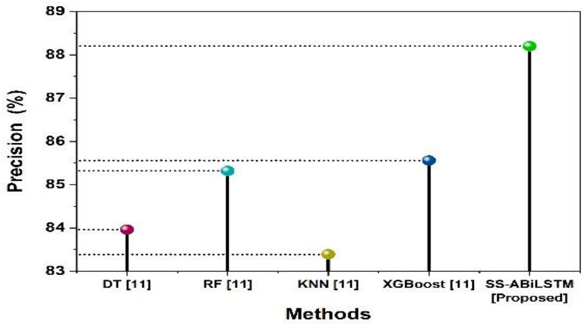

Figure 3 Result of precision

Recall: The number of samples that are appropriately identified as stressed is the metric. It is determined through mathematics. The comparison of recall among the existing approaches and proposed method is displayed in Figure 4. SS-ABiLSTM approach achieved 91.8% with existing methods attaining DT (81.63%), RF (84.44%), KNN (85.53%), and XGBoost (86.23%). It illustrates how SS-ABiLSTM might identify stress more effectively.

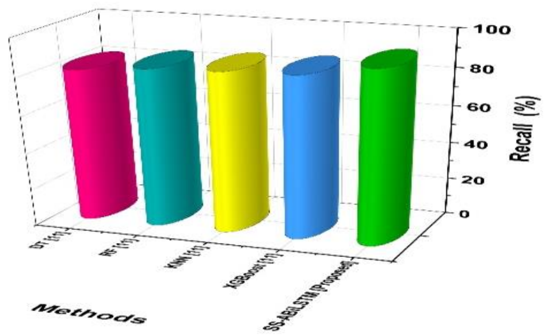

Figure 4 Assessment of recall

F1-score: This particular metric is better whenever the dataset is inconsistent while the minority class also contains significant amounts of content. It employs a harmonic average of accuracy and sensitivity. The comparison of F1 score among the existing approaches and proposed method is displayed in Figure 5. When compared to other existing approaches, proposed SS-ABiLSTM approach achieved 90.1% and existing methods such as DT (85.28%), RF (82.31%), KNN (83.37%), and XGBoost (86.21%). Result demonstrates the superior efficiency in stress classification using SS-ABiLSTM.

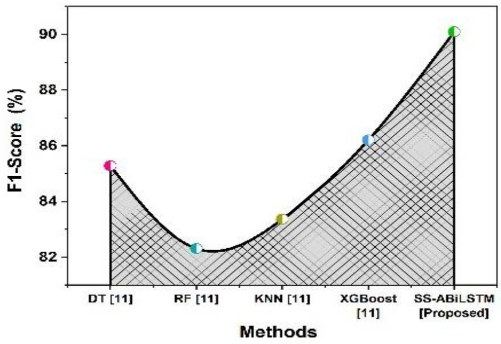

Figure 5 Comparison of F1-score

4. Conclusion and future scope

The study described public health as stress enhancing and used EEG data to develop stress valuation. Stress was an extensive health problem that exaggerated people in a variation of population density. The study proposed SS-ABiLSTM, an innovative method for improving stress evaluation by integrating EEG data. After gathering EEG data, the preprocessing techniques ensure that data are cleaned. DWT is used to extract features, which reliably extract frequency-domain information from the data. The most discriminative characteristics for stress assessment were determined by the RFE used to remove the unwanted data. Utilizing the application of SS-ABiLSTM, the method of public health addressed stress prevention and management while also improving the ability to interpret EEG data. The parameter metrics used in the study are F1-score (90.1%), precision (88.2%), recall (91.8%), and accuracy (98.97%). The accuracy for the proposed technique was superior to existing techniques. Finally, using EEG data for stress evaluation in public health showed potential for more individualized care and better mental health results. One of EEG's limitations is its inability to accurately assess neuronal activity that originates underneath the cortex, the brain's uppermost layer that is not able to pinpoint precise brain regions. Future scope for enhancing stress evaluation using EEG data includes real-time monitoring and using deep learning techniques for pattern recognition for early detection and targeted intermediations in public health.

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