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ORIGINAL ARTICLE

A novel technique for stress detection from EEG signal using hybrid deep learning model

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Abstract

Stress is burgeoning in today's fast-paced lifestyle, and its detection is imperative. An electroencephalography (EEG) technique is used to identify the brain's activities from the brain's electrical bio-signals. However, only a highly trained physician can elucidate EEG signals due to their complexity. This study proposes a DWT-based hybrid deep learning model based on Convolution Neural Network and Bidirectional Long Short-Term Memory (CNN–BLSTM), which detects stress levels in humans. Further supports neurologists, mental health counselors, and physicians in making decisions on stress levels. The Physionet EEG dataset is used to detect the stress level for mental arithmetic tasks. Noise from multi-channel (19 channels) EEG signals has been removed and decomposed into four levels using Discrete Wavelet Transform (DWT). After decomposition, an automatic feature selection method, namely Convolution Neural Network (CNN), is used on the decomposed signals. Finally, BLSTM is used to classify stress levels. The accuracy of the proposed model is compared with CNN-based Long Short-Term Memory (LSTM) and previous work. The results show that the proposed hybrid model achieved higher classification accuracy (99.20%) compared to others. Further, the stratified tenfold cross-validation technique is applied to validate the proposed model with a classification accuracy of 98.10%.

Keywords Electroencephalogram (EEG) · Discrete wavelet transform (DWT) · CNN · LSTM · BLSTM

1 Introduction

An electroencephalogram (EEG) signal is widely used to observe and measure the brain's electrical activity and record it as voltages. Stress has recently become a significant issue in advanced societies; as a result, a huge effect on the physical health and mental health of individuals has been noticed [1, 2]. People from various professions get influenced by stress. Indeed, negative stress can cause or exacerbate a variety of illnesses affecting the brain, immunological system, and endocrine system. Stress induces the release of cholesterol and triglycerides into the bloodstream, which increases heart rate and blood flow. Long-term stressors affected cardiac functionality [3], and early-life stressors have been associated with migraine and physical activity. Especially for people who have had just minor early-life stress [4], affected by stress, it is a chronic respiratory disease of unclear etiology and patients tend to show greater bronchoconstriction than healthy controls in response to stress [5].

In this regard, it is well known that positive and negative stress, like other brain activities, induce bioelectrical changes that can be monitored in several physiological systems. An EEG recording under the scalp measures the electrical activity in this portion of the brain. The use of artificial intelligence (AI) algorithms to efficiently analyse these EEG signals has been proposed, reducing the need for human interaction [6]. This paradox, "physiologic systems start by stress cannot protect only but harm the body", is said Selye over ninety years ago. Stress impacts everybody and has the potential to be a major health threat facilitating illness and disease. In this work, EEG signals are applied to classify the relaxed condition and stressed condition.

Previous research has decomposed EEG signals using the wavelet transform [7] and evaluated the performance using various machine learning and deep learning

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algorithms to detect stress and relaxation in EEG signals. In an attempt to solve the problem, various algorithms have been developed. EEG shares good compatibility among the stress signals. For stress detection from EEG signals, support vector machine (SVM) [8] a classification algorithm, has been proposed. A Hybrid model combination of BLSTM and LSTM is used for the classification of mental workload levels which achieved 86.33% [9]. LSTM is used for emotion recognition from multi-channel of EEG signal achieved 81.10% accuracy [10]. Four channels and five frequency band of EEG signals which are used by the four classification algorithms namely, stochastic decent gradient, logistic regression (LR), and multi-layer perceptron (MLP), sequential minimal optimisation are applied for stress classification. It is observed that LR outperforms other classification algorithms with the highest accuracy of 98.76% [11]. In the study [12], the author described a procedure to detect human stress levels based on physiological data. Binary and ternary classifiers are being developed based on the EEG-metric parameters. Using a multi-layer perceptron kernel-based SVM, the stress levels of 30 subjects have been correctly identified by a binary classifier, and the stress levels of 26 subjects have been correctly identified by a ternary classifier out of 41 subjects. In the study [13], authors developed a method to automatically predict stress using EEG data of construction workers. The data are being preprocessed to obtain high-quality signals. Using the fixed windowing approach and the SVM with Gaussian kernel yielded the highest classification accuracy of 80.32%. Our main contributions in this paper are summarised as follows:

- Raw EEG signals are preprocessed and extracted features using an efficient technique called discrete wavelet transform (DWT), which is applied to denoise and decompose them into five frequency bands. At low frequencies, DWT provides precise frequency information, whereas at high frequencies, it provides accurate time information. The combination of frequency and temporal study can be used to improve EEG studies [14]. One of the advantages of discrete wavelet transform (DWT) is to decompose the EEG signals (nonlinear and non-stationary component) into linear and stationary component. As a result, the DWT fit for the analysis of asymmetrical patterns of data.
- CNN intelligent paradigm is used for automatic feature selection from DWT extract frequency band.
- The BLSTM architecture is utilised for the classification of stress and relaxed situations. BLSTM is able to every component of an input sequence has information from both the past and present, for this reason BLSTM produced a more accurate results.
- Various challenging benchmark datasets are used to assess our proposed system. Unlike other anomaly detection methods, we achieve cutting-edge findings. DWT-based hybrid deep learning based on CNN–BLSTM model strategy reached 99.20% accuracy.

The remainder of the paper is organised as follows. The second section examines existing methodologies and their associated work, section three a description of the methodology framework proposed section four evaluates the results and experiments discussion. The conclusion of this research work has been written in section five with a comparison of existing techniques.

2 Related work

In this section, recent work held on stress detection using EEG signals is covered. The main objective is to find the EEG indicators that predict human stress and boost the detection rate. Lots of studies held on various features from different domains like time and frequency, as well as various machine learning models such as Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) are also applied to predict the stress level [15, 16], Table 1 shows the EEG signal's channel range (4–33) taken of subjects 15 to 48 and applies different feature extraction techniques and classifiers for analysis of stress and relaxation state with accuracy. Several ML models are continuously used for EEG signal study [11, 17–19]. Deep learning techniques outperform in EEG data classification compared to traditional ML models [9, 20, 21]

In the existing work [11], researchers considered four EEG channels and a classical machine learning model (called LR), which can be suitable for less featured datasets. Fatigue detection [22], driver stress detection [23], neurological status detection [24], and automated arrhythmia classification [25] are based on CNN and LSTM and achieve higher performance on different dataset. CNNs (or ConvNets) are neural networks mainly used for auto-correlated data processing [14]. The proposed model is used on a large dataset (19 EEG channels) to analyse stress levels.

3 Proposed methodology

EEG data collection, feature extraction, feature selection, and classification are the four processes in the proposed model. The DWT approach is used to eliminate noise and decomposed them into five frequency bands frequency band to extract features from EEG signals, and CNN is used for feature selection. Finally, to classify stress levels,

Table 1 Related work

EEG Dataset	Feature Extraction	Classifier	Accuracy (%)
10 channels are taken from 15 subjects [17]	Wavelet Entropy	LDA and SVM	84.9
33 volunteers, closed-eye condition [18]	Neuro-physiological features	SVM, NB, KNN, LR, and MLP	85.20
6 subjects of EEG Signals [19]	Hilbert Huang Transform (HHT)	SVM	89.07
4 channels are taken from 27 subjects [11]	Band Power	Stochastic decent gradient, (LR)	98.76
32 channels are taken from 32 subjects [20]	Band Power	LSTM	94.69
4 channels are taken [21]	OneR, Bayes Network	Random Forest (RF)	94.89

SVM, Support vector machine; NB, Naive Bayes; LR, Logistic Regression; KNN, K-nearest neighbour; LDA, Linear discriminant analysis; MLP, Multi-layer Perceptron

the BLSTM deep learning model is applied. Figure 1 shows the proposed framework.

3.1 Data acquisition

The collected dataset contains international 10/20 system recordings from 36 subjects while performing serial subtraction tasks. The mental readings were recorded in the form of EEG measurements taken before and after the cognitive activity performed by the subjects. The subjects were further divided into good and bad counters based on their performance and efforts in subtraction tasks. The 36 healthy volunteers, 9 male and 27 female in the age group of 16–26 years, were students of the Educational and Scientific Center "Institute of Biology and Medicine", National Taras Shevchenko University of Kyiv, Ukraine. The dataset was available through Physiobank [26].

Total 91000 (182 sec $\times$ 500 Hz) data points make up the baseline for the resting state, while 31000 (62 sec $\times$ 500 Hz) data points make up the stress induced data. It should be noted that the data acquired for both classes is unbalanced. The paper considered the first 62 seconds of the baseline. Each subject has 23 EEG channels of thirty-six subjects out of which 19 channels are consider in this paper. Each channel contains a sample rate of 500 Hz. Figure 2 shows electrode position for 19 channels classified as anterior frontal (Fp1, Fp2), frontal (F3, F4, F7, F8, Fz), central (C3, C4, Cz), parietal (P3, P4, Pz), temporal (T3, T4, T5, T6), and occipital (O1, O2). Every recording

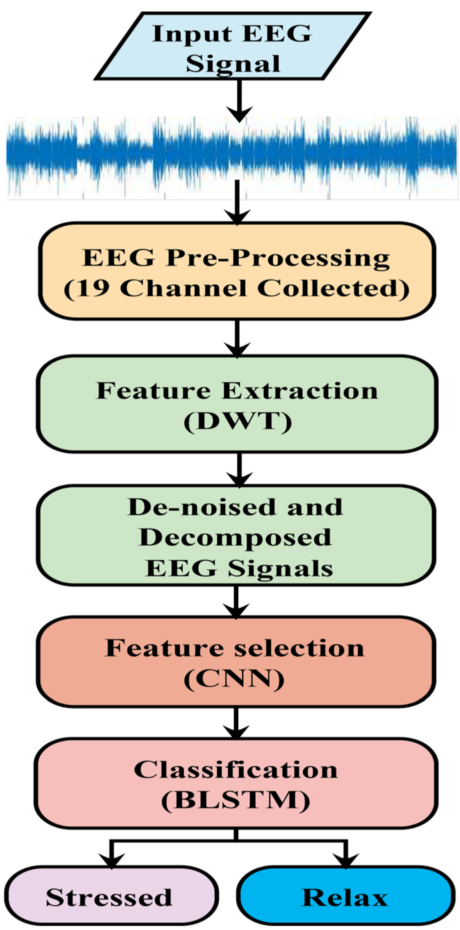


Fig. 1 DWT-based Hybrid CNN–BLSTM Model

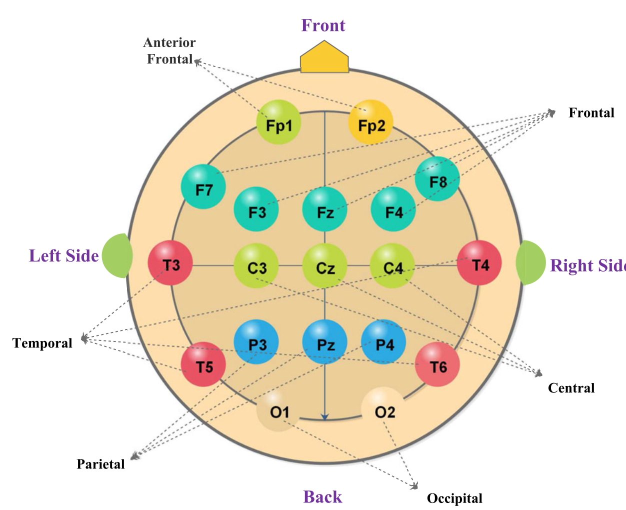


Fig. 2 EEG electrode positions on brain

includes an artefact-free baseline EEG of 182 seconds and a task-performing state of 62 sec, which is a stressful state. Table 2 shows the classification description of the dataset with descriptions of the EEG recordings considered.

In the dataset, total 19 channels and 1116000 (31000 × 36) data points per channel are taken into consideration, in which 70% of the data are used for training and the rest for testing. Furthermore, training data are also subdivided into 70:30 ratios for validation training and testing, respectively.

3.2 EEG feature extraction

Raw EEG signals suffer from poor spatial resolution, low signal-to-noise ratio, and artefacts [27]. The wavelet transform is currently widely used to remove noise from signals. DWT divides the EEG signal's input signal into detailed and approximation coefficients in different frequency bands to retrieve the frequency bands. The EEG signal is decomposed by continually separating it into two bands using a high-pass filter and a low-pass filter until the desired level is reached. This work extracted five frequency bands from each channel.

3.2.1 Discrete wavelet transforms (DWT)

The wavelet transform (WT) is a powerful tool for signal processing and is broadly applied in biomedical engineering fields for solving many real-life problems. It is a wave-like vibration with an amplitude that rises and falls over a time period of approximately zero. WT can also be used in wavelet-based decomposition techniques to reduce data loss and restore raw data [28, 29]. WT is best fitted for the analysis of asymmetrical data patterns, such as impulses occurring at various time instances [30]. The continuous wavelet transform (CWT) of a signal, *s*(*t*), is defined as the signal's integral multiplied by scaled and shifted versions of a wavelet function ψ, shown in Eq. (1).

$$CWT(y,z) = 1/\sqrt{|y|}\int_{-\infty}^{\infty} s(t)\psi((t-z)/y)dt. \tag{1}$$

where y and z are called the scaling and shifting parameters, respectively. Calculating wavelet coefficients at every possible scale is a computationally very expensive task. Instead, if the scales and shifts are selected based on powers of two, so-called dyadic scales and positions, then the wavelet analysis will be much more efficient. Such analysis is obtained from the DWT which is defined as

$$DWT(c,d) = 1/\sqrt{2^c}\int_{-\infty}^{\infty} s(t)\psi((t-d2^c)/2^c)dt. \tag{2}$$

where y and z are replaced by differences of information available on two successive resolution 2^c and $d2^c$, respectively [31]. The computing of wavelet coefficients at all scales is a time-consuming procedure. The wavelet analysis will be significantly more systematic if the scales and shifts are chosen based on powers of two.

The DWT method decomposes a signal into approximation and detail coefficients to provide the first level of decomposition. The approximation coefficients of each level are further subdivided into approximation and detail coefficients of the next level [32]. This research work used DWT on each EEG channel to extract the five-band frequency and denoised signal using a mean and median filter. Figure 3 shows the wavelet decomposition process in the four levels by Low-Pass (LP) and High-Pass (HP) filter coefficients. Approximation coefficients are A1 (0–32 Hz), A2 (0–16 Hz), A3 (0–8 Hz), A4 (0–4 Hz, Delta), and detail coefficients are D1 (30–65 Hz, Gamma), D2 (14–30 Hz, Beta), D3 (8–14 Hz, Alpha), and D4 (4–8 Hz, Theta).

The multi-resolution analysis offers data on the signal across multiple frequency bands. The EEG channels of 36 subjects were extracted using EDF browser and processed dataset during the data preprocessing step. To extract five physiological EEG frequency bands, four levels of DWT with an eight-order Daubechies (db8) wavelet function have been used. Table 3 represents the frequency band of the EEG signal using fourth level decomposition.

3.3 Convolutional neural network (CNN)

The goal of these methods is to find and use specific features among the features extracted from the model's layers. In other words, it aims to create a subset of better features

Table 2 Datasets description

Classification on metal workload	Number of subjects	Gender	Age group	EEG recording
Good	26	6 Male, 20 Female	16–26 years	19 Channels with a sample rate of 500 Hz per channel, 62 seconds recording, therefore in total (62s*500) 31000 data point in each channel is considered for mental counting
Bad	10	3 Male, 7 Female		

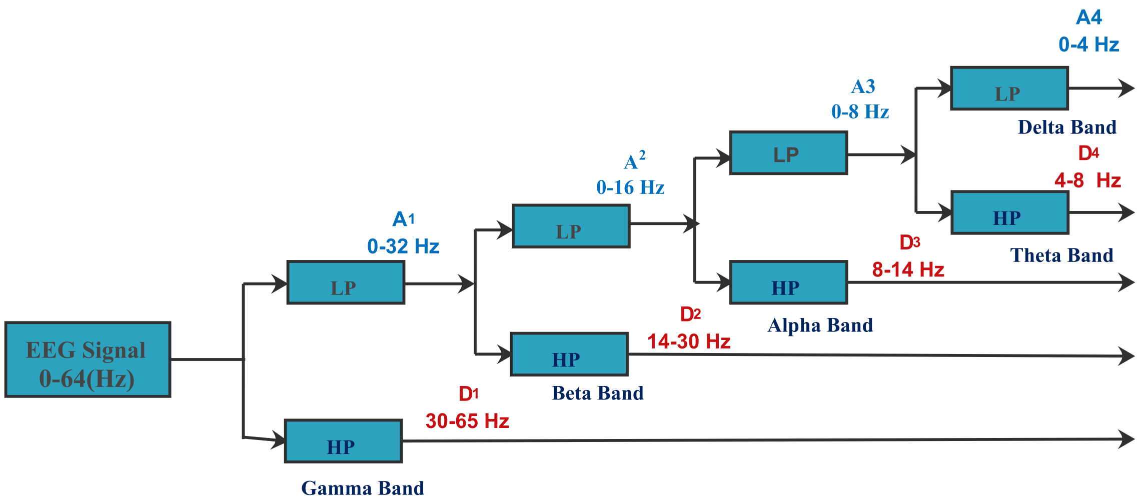


Fig. 3 Wavelet coefficients sequence of filters decomposition according to EEG range

Table 3 Frequency band of the EEG signal using fourth level decomposition

Frequency range (Hz)	Wavelet sub-band	Decomposition steps	Band name
30–65	D1	1	Gamma
14–30	D2	2	Beta
8–14	D3	3	Alpha
4–8	D4	4	Theta
0–4	A4	5	Delta

from the existing feature set. It improves the accuracy of a model if the proper subset is chosen, and it also reduces over-fitting. In this study, CNN is used to extract characteristics from the EEG frequency band. CNNs are neural networks that are primarily used to process auto-correlated data [14]. CNNs are built around filters, also known as kernels, which use convolutional operations to extract relevant features from input. CNNs typically display several specialised hidden layers with varying functions and hierarchies, i.e. the first hidden layers detect simple patterns, the next layers identify patterns, and the final hidden layers are specialised and can recognise complex patterns. Deep learning uses a multi-layered neural network to extract characteristics from data and improve data identification and classification over time.

CNN architecture is shown in Fig. 4. In this research, two layers of CNN are used in a sequential model. In this architecture, the first layer of CNN takes input from pre-possessed EEG data to extract relevant features using convolutional operations and the softmax activation function. The maximum value from each cluster of neurons in the first layer is used in the max-pooling layer. Every neuron in one layer is connected to every neuron in the next layer via fully connected layers [33]. The maximum values of max-pooling are used as input for the second layer of CNN. The operations of second layer CNN are similar to those of first layer CNN.

3.4 Classification techniques

- Long Short-Term Memory (LSTM)

LSTM is an extension of recurrent neural networks (RNN), which is designed to solve the problem of vanishing and exploding gradients. A deep neural network-based classification technique was applied for stress detection on the EEG dataset [11]. LSTM can manage the long-term dependency problem in RNNs as well as the disappearing and expanding gradient issues, LSTM is better to RNN model [33, 34]. In this work, a combination of CNN with LSTM model applies to EEG signal to find out the stress and relax. At time $'t_i'$, the LSTM equations are written as follows:

$$G_t = \sigma\left(R_f * [h_{t-1}, x_t] + B_f\right) \quad (3)$$

$$H_t = \sigma(R_i * [h_{t-1}, x_t] + B_i) \quad (4)$$

$$I_t = \sigma(R_o * [h_{t-1}, x_t] + B_o) \quad (5)$$

$$C_{t1} = tanh * (R_c * [h_{t-1}, x_t] + B_c) \quad (6)$$

$$C_{t2} = G_t * C_{t1-1} + (1 - G_t) * C_{t1} \quad (7)$$

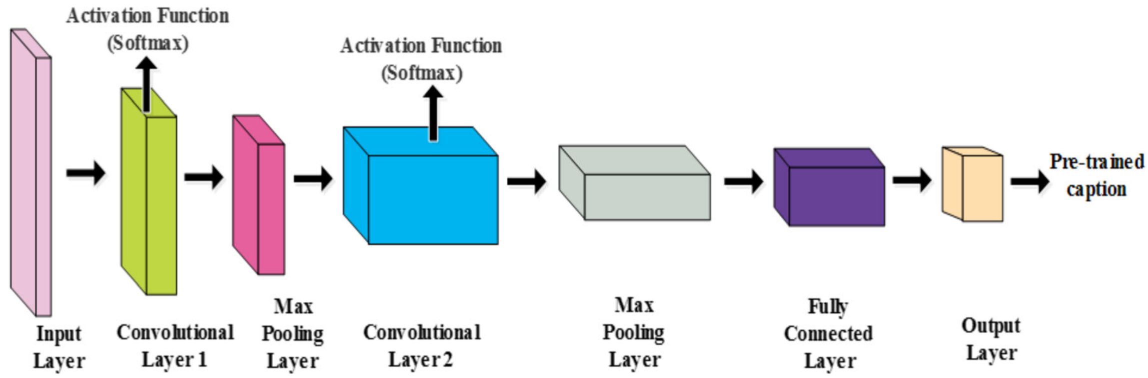


Fig. 4 CNN layer architecture

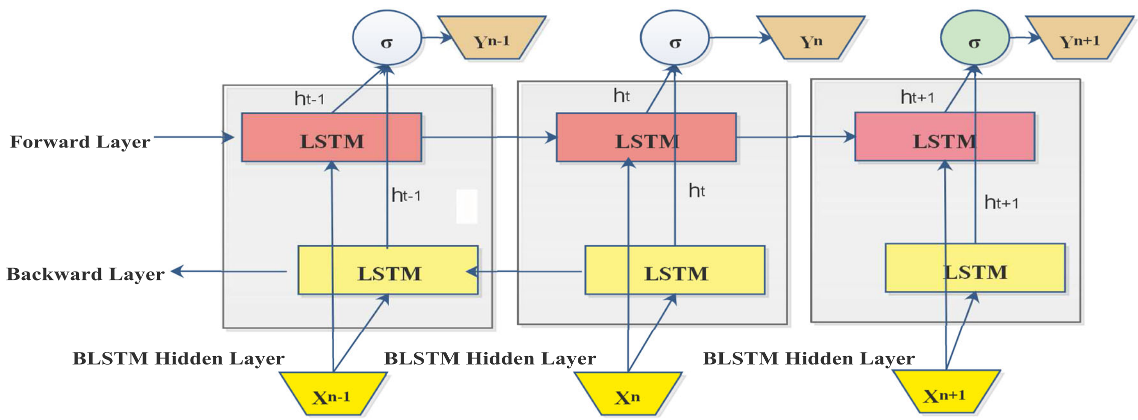


Fig. 5 Architecture of Bidirectional LSTM with three consecutive steps

$$h_t = I_t * tanh(C_{t2}) \quad (8)$$

G_t, H_t and I_t represent forward, input, and output gates, respectively, shown in Eqs. 3, 4, 5. C_{t1} and C_{t2} are cell states and candidates, respectively, shown in Eqs. 6, 7. R and B are the weight and bias matrices for the respective gates. Function tanh is the hyperbolic tangent function, and σ is the sigmoid function shown in Eq. 8.

- Bidirectional LSTM (BLSTM)

BLSTM adds an additional LSTM layer that reverses the flow of sequence of information. The outputs from both LSTM layers are then combined in a variety of methods, including average, sum, multiplication, and concatenation. The main reason behind choosing BLSTM is that every element of an input sequence contains data from both the past and the present. As a result, by integrating LSTM layers from both directions, BLSTM generates more accurate output. BLSTM looks complicated, but the results are in a good direction due to a proper understanding of the environment. This research utilises multi-layer BLSTM, in which each layer comprises two cells, which contain information about forwarding and backward passing, respectively [35]. The multi-layer BLSTM is fed with the output extracted from the ResNet-50, in the form of feature chunks for inconsistency detection. The initial frame with a chunk of 1000 features is given as input to multi-layer BLSTM at an instance time 't', while the other chunk is queued to be given at '$t + 1$' instance of time and so on. In Fig. 5, the architecture of BLSTM with three consecutive steps, where X and Y are represented as inputs and outputs, respectively, and σ for the activation function.

3.5 Proposed hybrid CNN–BLSTM model

The automatic feature selection by CNN has the largest overall contribution to the feasibility, and BLSTM is that every element of an input sequence contains data from both the past and the present; for these reasons, this study chooses a hybrid deep learning CNN–BLSTM. The proposed model consists of two stacked one-dimensional CNNs with 95 and 47 neurons each set for filters to detect hidden patterns in the dataset, activation function softmax, and kernel moves on the input data by its size. Kernel's size 2 tuned for both layer and padding valid, respectively. The first CNN layer takes the preprocessed EEG signals as input. A max-pooling layer is used between the first and second layers and after the second layer of CNN with a batch size of 2. A pooling operation chooses the most significant element from the feature map region covered by the filter. The next Bidirectional LSTM (BLSTM) layer is used with 64 neurons. The BLSTM layer's output is taken as input for the dropout layer with 0.5 rate. Finally, a dense layer applied with 1 neuron and activation function sigmoid has been used for the classification of stress and relax state. The parameters are tuned by the hit and trial method. The proposed model's training hyper parameters are described in Fig. 6.

To avoid the problem of over-fitting during the learning process, proper parameter tuning for each layer and regularisation using the dropout layer have been implemented in the proposed system. The parameters of the CNN softmax activation function are tuned on both layers, and the sigmoid activation function learns to be more reliable for each layer, which improves classification. After feature maps by each layer system become more generalised to produce better outcomes, each layer of CNN and BLSTM extracts temporal information from the input signal.

Algorithm 1 Proposed algorithm for Stress detection

Results: Different activities recognition using precision, f1-score, sensitivity, specificity, classification accuracy, positive likelihood ratio (+LR), negative likelihood ratio (-LR), negative predicted value (NPV) and ROC curve;
Input: Dataset of EEG signals data from Physionet EEG during mental arithmetic tasks [26].
Output: Predict Stress Labels (Person in Stress or Relax);
Procedure:
Step 1: Extract the features from the EEG signal channel data DWT:
  1.1 Remove noise from signals;
  1.2 Eight-order Daubechies (db8) wavelet function is selected for analysis;
  1.3 The four levels are decomposed into different frequency;
  1.4 Extract the frequency band are Alpha, Beta, Gamma, Delta, Theta;
Step 2: Apply an automatic feature selection in multi-channel EEG signals using Convolution Neural Network (CNN);
Step 3: Use BLSTM, a deep learning model with 100 epochs, for classification;
Step 4: Generate and store obtained precision, f1-score, sensitivity, specificity, classification accuracy, positive likelihood ratio (+LR), negative likelihood ratio (-LR), negative predicted value (NPV) and ROC curve;
Step 5: Repeat Step 3 and Step 4 for the CNN-LSTM model for comparison with the proposed model;
end

4 Results and discussion

This section presents the different results and discussions of the proposed model, the machine learning model, and the deep learning model. The proposed model has been tested and compared on Physionet EEG during the mental arithmetic tasks dataset [26].

4.1 Performance analysis

The proposed DWT-based hybrid deep learning based on CNN–BLSTM model is compared with CNN-LSTM deep learning model to prove the better efficiency of CNN–BLSTM. Both models consist of the same denoised and decomposed inputs, parameter tuning, regularisation and are compared with a loss function (binary cross-entropy) and an optimiser (Adam). The proposed model and CNN-LSTM have been trained with 100 epochs, and considered batch size is 20. The outcomes of the proposed model are analysed using the evaluation metrics accuracy, sensitivity, $F1$-score, specificity, Negative Predicted Value (NPV), precision, or Positive Predicted Value (PPV), Positive

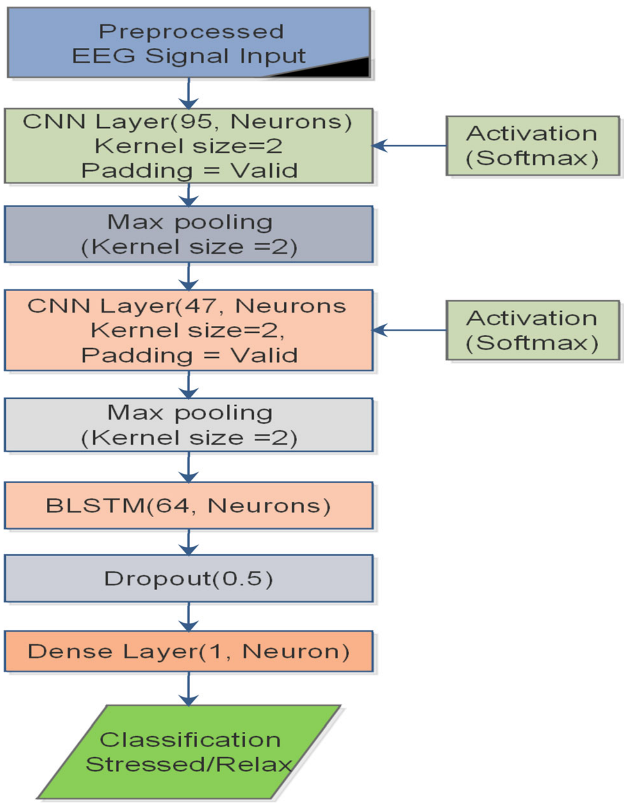


Fig. 6 Training Hyper Parameters CNN–BLSTM

Likelihood Ratio (+LR) and Negative Likelihood Ratio (−LR) on the EEG dataset. Figure 7 shows confusion metrics for two class (stress and relax) based upon the classification results for EEG testing data and formulation of the above-mentioned confusion matrix parameters is depicted in Table 4.

Model comparison analysis on different parameters is shown in Table 5 and finds the better results of the above-mentioned parameters. As an example, the CNN–BLSTM precision value or PPV (98.40%) is better than that of CNN-LSTM (97.20%) which indicates the ratio of correct positive predictions out of all positive predictions. Similarly, the sensitivity (98.50%) value is also better than other models, which indicate the ratio of correct positive predictions. F1-score value, specificity value, and accuracy value provides better significant result than CNN-LSTM.

True Class	Predicted Class		
	Stress	Relax	Total
Positive	True Positive(TP): 91299	False Positive(FP): 1456	TP+FP: 92755
Negative	False Negative (FN): 1360	True Negative(TN): 240685	FN+TN: 242045
Total	TP+FN:92659	FP+TN:242141	

Fig. 7 Confusion matrix with predicted value

For a dichotomous test, the likelihood ratio (LR) is defined as the likelihood of a test result in subjects with the stress divided by the likelihood of the test result in relax [36]. This test +LR is 164 which is greater than one with 95% confidence interval (CI) range [156,172] and −LR is 0.01, which is less than one with 95% CI range [0.01,0.02].

4.2 Performance analysis using receiver operating characteristic (ROC) curve

The receiver operating characteristic (ROC) curve measures how accurately the model can distinguish between stressed and relaxed states.

The performance measure using confusion metric is not adequate as a large number of irregular data in the dataset. ROC curve is used to get the number of true positives and false positives on test data. ROC curve has been plotted between the false positive rate on the *X*-axis and the true positive rate on the *Y*-axis. Figure 8 gives ROC curve for the proposed model and CNN-LSTM model. ROC covered area (area under curve) for the proposed model is higher than that for the CNN-LSTM model, which indicates the better performance of the proposed model.

4.3 Convergence curve analysis

A convergence curve for the training and validation phase shows the optimal value of the learning parameter with the model's accuracy with respect to the loss function. The training and validation accuracy traces of the CNN–BLSTM and CNN-LSTM models from 100 epochs is shown in Fig. 9a and b, respectively. The proposed model's training and validation accuracy shows a better convergence rate and achieve higher accuracy of 99.20% compared to the developed CNN-LSTM model.

4.4 Analysis of proposed and existing works in comparison

This section compares the proposed work to previous machine learning models based on the EEG channels employed and feature selection methods used. Different studies have also focused on detecting relaxation and tension from EEG signals in the literature. In the EEG dataset, there are a total of 22 channels and 19 channels obtained from 36 patients for LSTM model [33, 35].

A window segmentation technique was applied for feature selection, and LSTM architecture was used for classification and achieved 91.67% accuracy. Band power ratio technique is applied for feature selection, and the machine learning models SVM and NB are used for classification to achieve 96.967% and 94.60% accuracy, respectively [37–39]. In the proposed work, we analysed

Table 4 Confusion matrix parameter calculation

Parameter	Formula
Precision or Positve Predicated Value(PPV)	$\frac{TP}{TP+FP} * 100$
Recall or Sensitivity	$\frac{TP}{TP+FN} * 100$
Specificity	$\frac{TN}{FP+TN} * 100$
Negative Predicted Value(NPV)	$\frac{TN}{FN+TN} * 100$
F1-Score	$\frac{2*(PPV*\text{Sensitivity})}{PPV+\text{Sensitivity}} * 100$
Accuracy	$\frac{TP+TN}{TP+FN+FN+TN} * 100$
Positive Likelihood Ratio(+LR)	$\frac{\text{Sensitivity}}{100-\text{Specificity}}$
Negative Likelihood Ratio (-LR)	$\frac{100-\text{Sensitivity}}{\text{Specificity}}$

Table 5 Model comparison metrics

Combinational approaches	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Precision Or PPV(%)	NPV(%)	+LR	−LR
CNN-LSTM	96.70	98.30	92.70	97.70	97.20	92.70	13.46	0.018
CNN–BLSTM	**99.20**	**98.50**	**99.40**	**98.40**	**98.40**	**99.40**	**164**	**0.01**

Bold indicates proposed model technique

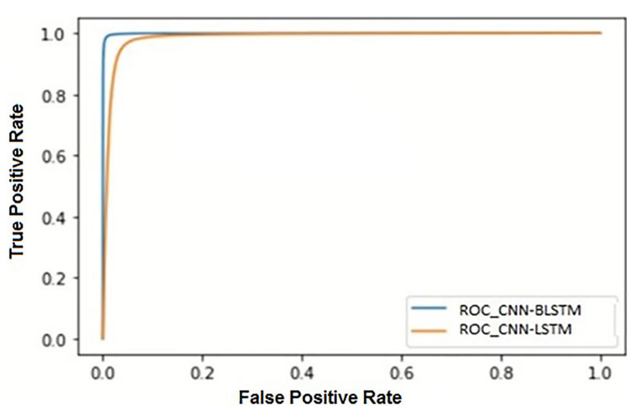


Fig. 8 ROC of (CNN–BLSTM) and (CNN-LSTM) Classifiers

only 19 EEG channels of 36 subjects in the dataset. DWT is used to extract features after removing noise. CNN-based automatic feature selection method is applied to identify the feature and a BLSTM deep learning model is used for classification to get 99.20% accuracy [37, 38]. The proposed work is also compared with other models and is shown in Table 6, Metrics parameters of the proposed model and other models are shown in Fig. 10.

The number of samples used for training and testing has a significant impact on the output of a classifier. Previous works achieved accuracy based on various channels, subjects, and feature extraction/selection methods. For example, total of 19 EEG channels, selected from 36 subjects [30], using band power ratio techniques for feature extraction and SVM and KNN machine learning models for classification, achieved an accuracy of 96.96%. In this paper, considering 19 channels from 36 subjects, on applying DWT for feature extraction, an automated feature selection using CNN, CNN-based BLSTM deep learning model for classification, outperforms the previous models and obtains an accuracy of 99.20%.

4.5 Validation of classification models

Predictive models are built on a dataset and then evaluated using resampling procedures to get quantitative statistical results. Finally, statistical analysis is performed to choose the best model possible [41]. This work used a stratified tenfold cross-validation method for training and testing on CNN–BLSTM and obtained an average classification accuracy of 98.10%.

5 Conclusion

In this study, we proposed a DWT-based hybrid deep learning model based on Convolution Neural Network and Bidirectional Long Short-Term Memory (CNN–BLSTM) for stress detection using EEG signal. The dataset contains the EEG readings of people before and after performing an

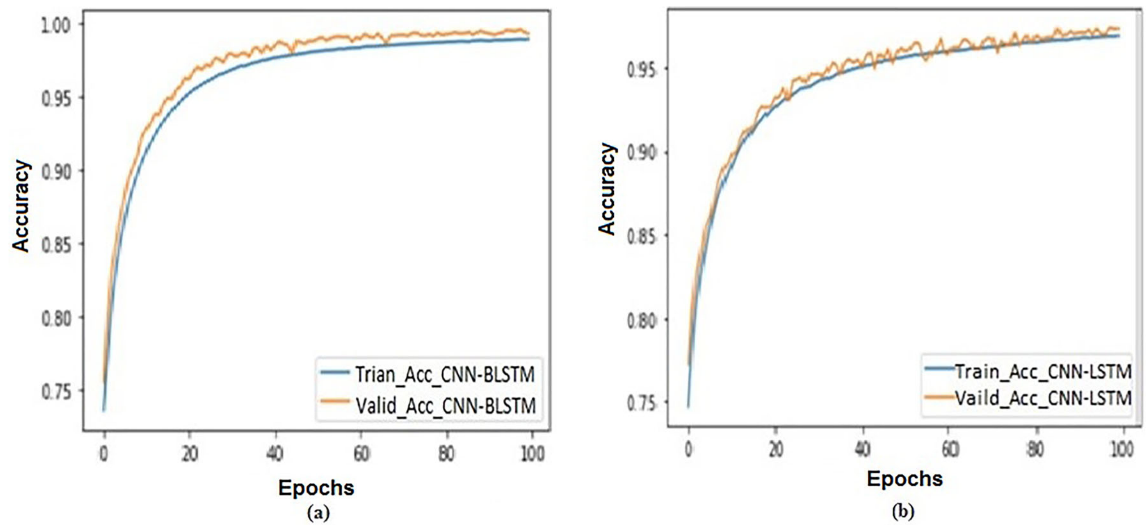


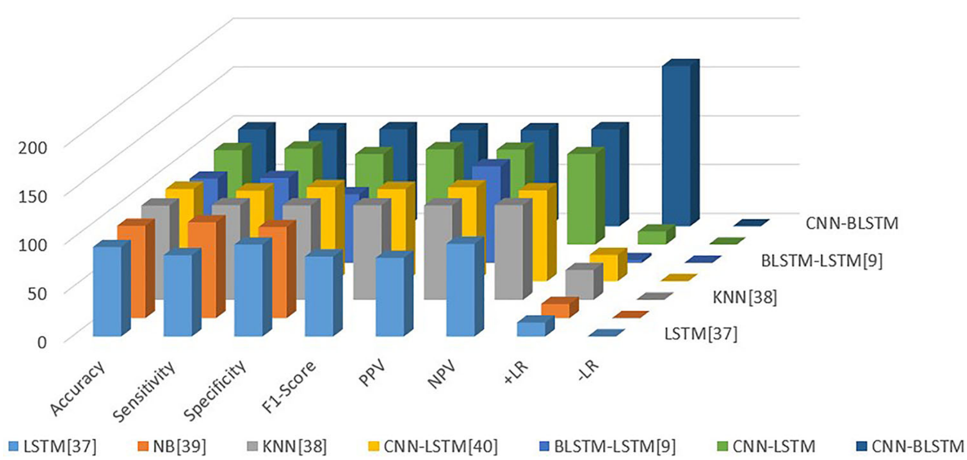
Fig. 9 **a** Training and validation accuracy of CNN–BLSTM and **b** CNN-LSTM

Table 6 A comparison with the most recent articles on stress detection using EEG signals

EEG Dataset	Models	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Precision Or PPV(%)	NPV(%)	+LR	−LR
Total 22 EEG considered channels from 36 subjects [37]	LSTM	91.67	83.33	94.22	81.88	80.56	95.00	14.41	0.17
Total 128 EEG channels considered from 22 subjects [39]	NB	94.60	98.30	93.30	–	–	–	14.67	0.018
Total 19 EEG channels considered from 36 subjects[38]	KNN	96.60	97.00	96.80	96.9	96.8	97.00	30.31	0.030
Total 28 EEG signals obtained from 15 subjects [40]	CNN-LSTM	94.83	93.10	96.55	94.75	96.43	93.33	27.10	0.071
Total 14 EEG channels considered from 48 subjects [9].	BLSTM-LSTM	86.33	86.88	70.59	–	98.91	–	2.95	0.18
Total 19 EEG channels considered from 36 subjects.	CNN-LSTM	96.70	98.30	92.70	97.70	97.20	92.70	13.46	0.018
Total 19 EEG channels considered from 36 subjects(Proposed)	**CNN–BLSTM**	99.20	98.50	99.40	98.40	98.40	99.40	164	0.01

PPV, Positive Predictive Value; NPV, Negative Predictive Value; +LR, Positive Likelihood Ratio, −LR, Negative Likelihood Ratio

Fig. 10 Comparison between existing approaches and proposed model



arithmetic task [26]. DWT is used to denoise and decompose the EEG signals which removes nonlinearity and nonstationary within the signals. The denoised and decomposed signals have been used as the inputs in the sequential deep learning model, CNN–BLSTM. It is observed that in the proposed algorithm, the automatic feature selection by CNN has the largest contribution to the feasibility, and BLSTM is able to extract information from both past and present components of an input sequence; for these reasons, CNN–BLSTM produces a more accurate results. The model achieved 99.20% classification accuracy for stress detection. The proposed work is also compared with the CNN-LSTM model. In future work, a proposed automatic feature extraction based hybrid model will be tested with other datasets of different disease prediction tasks.

Availability of data https://physionet.org/content/eegmat/1.0.0/.

Declarations

Conflict of interest Author Lokesh Malviya declares that he has no conflict of interest. Author Sandip Mal declares that he has no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

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