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Original Article

A Parallel Fusion RNN-LSTM Approach to Classify Mental Stress using EEG Data

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Abstract - *Preventing and physiological healing problems need early stress diagnosis and a participant's predisposition to operate healthily under stress. Traditional methods of evaluating anxiety levels, such as interviewing the person and having to ask strain-based queries to develop a better understanding of their situation and observing facial gestures - individuals under stress respond by changing their brows, pupils dilating, or one's flashing strobe percentage could differentiate - are limited even though they may overlook stress episodes. Electroencephalogram (EEG) is a newly created physiological measure that has the potential to be utilized as a stress gauge in everyday life. It is due to the commercial availability of EEG headsets for studying brain activity conveniently and cost-effectively. This investigation used machine learning methods to classify stress status using resting-state EEG signal recordings. The method was tested using a dataset from the MathWorks® EEGLAB toolbox, and a dataset of 20 patients was constructed using a questionnaire and Neurosky's Mindwave EEG headset. For stress detection, a support vector machine (SVM), recurrent neural network (RNN), long short-term memory (LSTM), and a novel technique based on a parallel fusion of RNN-LSTM are used. The results of the MATLAB simulations show that the proposed technique is faster and more accurate than other machine-learning approaches. The proposed technique has a 95% accuracy rate, up to a 15% improvement over other results.*

Keywords - *Stress detection, EEG signals, machine learning, EEGLAB toolbox, Meurosky's Mindwave EEG headset, MATLAB.*

1. Introduction

Mental stress, a psychological phenomenon that mirrors the body's innate defences against predators and danger, has become more prevalent in recent years due to its prominence as the most pressing societal issue of the twenty-first century, particularly during the Covid-19 epidemic [1-4]. It is important to diagnose mental stress early on. It is important to diagnose mental stress early on to avoid any significant health complications due to it [5]. Stress may be detected and quantified using a variety of techniques and procedures, including Positron Emission Tomography (PET), electrocardiogram (ECG), Electromyography (EMG), and magnetic resonance imaging (MRI) [6], [7]. EEG is a medical procedure that measures the physiological features produced by electrical activity in the brain [8], [9]. EEG is the greatest alternative over ECG, EMG, PET, and Functional magnetic resonance imaging for faster, less expensive, and much more approachable insight into brain processes and high time resolution. EEG has become a vital tool since it is based on a non-invasive technique that uses stress hormones as input, allowing it to be utilized as a precise and trustworthy tool for stress calculation in cognitive and neuroscience research [10]. With the use of a revolutionary machine-learning algorithm, mental stress is recognized using EEG data in this study.

Stress is described as a state of high pressure and mental strain in layman's words., but it is defined in research studies as a bodily mechanism that responds to a challenge or a body reaction to mental, emotional, or physical suffering [11-12]. The fight-or-flight response is the name for this system. It also partially or completely impacts the practicality of everyday labour and the country's economy [13].

Because there is little time to rest between trials, stress can cause mental and behavioural changes [14], [15]. These alterations represent stress symptoms. Perspiration, spasms, dizziness, headaches, hypertension, muscular pains, and night terrors are all common symptoms; difficulties are examples of physical symptoms, whereas psychological symptoms include rage, nervousness, sadness, memory disorientation, mood swings, and melancholy [16-17].

Food cravings, abrupt furious outbursts, greater cigarette or alcohol usage, and frequent sobbing have all been recognized as important stress symptoms in stressed individuals [18]. Stress might not only produce dysfunctional behaviour, but it can also increase hypertension, cardiovascular disease, and gastrointestinal disease if it lasts for a long time [19-20].

As a result, researchers must recognize tension at a preliminary phase, and individuals must be aware of the implications of being over-stressed before it causes substantial health difficulties [21–23]. Stress harms human health and impairs the immunological system [24–26]. As a result, the scientific community is concentrating on determining the best method for recognizing stress early on to prevent it from becoming chronic and providing solutions to avoid irreparable harm [27–30]. To help society, low-cost, precise, and efficient technologies for emotion recognition and mitigation approaches are needed in healthcare, educational, scientific, military, science, athletics, or social activities are some of the areas where the government and industry intersect [31].

Various methods for assessing and studying stress levels have been produced, including questionnaires, assessments, and surveillance of people to quantify changes in physiological signals [32–34]. Physiological signals can be recorded and processed with greater precision in online real-world applications for the measurement of anxiety, which may be split into two subgroups:

- “Invasive type” and
- “Non-invasive form” [35].

Invasive treatments have drawbacks in some approaches, such as testosterone analysis, necessitating the development of non-invasive, efficient, precise, and trustworthy technologies [36]. The following techniques, which may detect stress through individual physiological data, are classified as non-invasive procedures [37–40]. EEG is the greatest choice over other non-invasive technologies for faster, cheaper, and more accessible insights into brain activities with a tight temporal resolution [41–44]. Small metal discs with thin wire electrodes are placed on the scalp, and impulses are sent to a device that records the information [45]. Due to the rapid nature of these electrical changes, precise temporal precision on the microsecond order may be attained [46]. The graphs of the brain's electrical energy versus time are mentioned in [47-48].

In this work, mental stress is detected using EEG signals using a parallel fusion RNN-LSTM-based novel machine learning algorithm. Conventional machine learning algorithms like SVM, RNN, and LSTM are compared with the proposed algorithm for performance evaluation. MATLAB EEGLAB toolbox is used as a platform to train and test the algorithms. An EEGLAB dataset of 20 EEG signals was created using Neurosky’s Mindwave EEG headset on sample patients. The suggested method appears to outperform standard algorithms, according to the results.

This research elaborates on EEG signals in section - 2 following the introduction from section - 1. Section - 3 describes conventional algorithms applied to EEG devices. The proposed method of the RNN-LSTM approach is described in section - 4. Furthermore, the result-oriented discussion with a conclusion and future scope are incorporated in sections 5 and 6, respectively.

2. EEG Signals

2.1. EEG Features

EEG activity is a temporal summation of the synchronized activity of millions of precisely coordinated neural cells. EEG analysis and interpretation are both an art and a science. The typical EEG has a wide range of physiological variability and is quite variable. When evaluating the waveforms in an EEG recording, it's critical to use a systematic approach. Even before beginning the analysis, one must know numerous confounding factors, such as the patient's age, level of awareness, the existence of muscle function, and the presence of various biological, ecological, and pharmaceutical drugs that may impact the waveforms.

The position, magnitude, duration, structure, consistency (periodic, sporadic, or constant), synchronization, symmetrical, and responsiveness of EEG waves may all be used to classify them. δ (Delta)-type operates between 0.5 to 4 Hz, θ (Theta)-type operates between 4 to 7 Hz, α (Alpha)-type operates between 8 to 12 Hz, γ (Gamma) -type operates between 12 to 16 Hz, and β (Beta) -type operates between 13 Hz to 30 Hz. Other frequencies beyond the typical spectrum of clinical EEG, such as ultra-slow oscillation (less than 0.5 Hz) and elevated oscillations (higher than 30 Hz), have lately acquired clinical value with the rise of digital signal analysis.

2.2. Measurement of Frequency

The typical spectrum of industrial EEG focuses on pulses with wavelengths ranging from 0.5-70 Hz. The EEG recordings are subjected to commonly related filtering for this study. A larger EEG gamut, but at the other extreme, has been researched by medical groups and academics and has been proven clinically meaningful in specific situations. When the infra-slow or ultra-fast portions of the frequency range are removed from normal EEG, several physiological and pathologically significant characteristics of cerebrum activity are lost. A full-bandwidth EEG (FbEEG) examines all biologically and therapeutically significant waveforms without making any compromises that favour one frequency range over another. Conversely, collecting EEG data at extremely high frequencies is not common in clinical practice since it requires specialized equipment to acquire data with higher sampling rates, doubling the amount of storage space required. EEG waveforms may be classified into several kinds based on the FbEEG recording: -

Intradural oscillation (ISO) (just under 0.5 Hz): ISOs are indeed the dominant frequency in preterm newborns, and they range from 0.01 Hz to 0.1 Hz. It is also known as spontaneously activity transients (SAT). It is endogenous cannabinoids driven, spontaneously activities that are critical in forming neural connections at such an early infantile stage when sensory information is minimal.

Furthermore, during non-REM sleep, ISOs across the 0.02 to 0.2 Hz frequency range are observed, phase synced with high frequencies EEG activity.

The majority of low-frequency EEG research has focused on conditional activation causal negative variability, motor motions, and the orienting paradigm. The amplitude of these slow scalp-recorded potentials is frequently only a few microvolts, necessitating Fb-EEG-based electrodes and skin-based electrode connections for true DC-type characteristics for reliable audio-based recording. Furthermore, spasms are associated with very sluggish EEG reactions and varied limited oscillations near the epileptic foci, according to invasive and non-invasive EEG tracking in animal studies and people. Non-invasive epileptic DC measurements recently revealed that localized onset episodes are associated with protracted and rather large DC changes.

1. δ- within the range of 0.5 Hz to 4 Hz: δ-rhythm is physically noticeable in profound slumber and is prevalent in about identical head locations. A faulty rhythm develops in waking states in situations of extensive neurodegeneration and targeted neurodegeneration. Adults have frontal intermittent rhythmic δ-activity, whereas the children's occipital rhythm is infrequent. Patients with status epilepticus typically have temporal interspersed rhythm δ activity (TIRDA).

2. θ- within the range of 4 Hz –7 Hz: This is the cadence that is set off by exhaustion in the early stages of sleep, such as N_1 and N_2. Linked to premature sleepiness, it is most pronounced in the inferior frontal brain zones and gradually makes its way rearward, replacing the α-cluster. In youngsters and early adulthood, elevated emotional moods can also improve prefrontal cyclic θ rhythm. During waking states, localized θ The presence of activity is a sign of localized brain dysfunction.

3. α-(8–12Hz): In typical awake EEG recordings in the frontal head area, the dominant anterior groove is typically present. It is the characteristic element of the adult EEG recording's regular ambient frequency. In healthy people, the anterior rhythm reaches the α-range of 8 Hz at the age of 3 years but does not diminish only until the 9th decade of life. Rapid variants of the atmospheric beat have been identified in the regular populace. The backstory's lowering is regarded as a sign of widespread brain damage. The rhythms fluctuate from patient to patient and from time to time within such a single individual. The α-rhythm's reactivity is a distinguishing feature that aids in its identification. It is most visible when the eyes are open, the mind is relaxed, and it is often diminished when the eyes are opened and mental effort is exerted. Patients with widespread encephalopathy may have generalized α-activity, which is non-responsive to internal stimuli and is known as "α-coma".

   μ-rhythm is a sort of α-rhythm with an arch-like architecture that appears in the central head regions. This pattern often ceases with contralateral limb motor action or thought about commencing the motor activity. Eye-opening, on the other hand, is mostly unaffected. Young individuals are the most commonly affected, whereas adults and children are less affected. Insomnia, sensorimotor stimulus, and mathematical ability are all variables that reduce the effectiveness of the treatment. On both ends, they are very uneven and inconsistent.

4. γ-Waves: sleep patterns, also known as σ-waves, are a type of activity that occurs medically during N_2 sleep. They are mainly noticeable in the fronto-central head areas and might be sluggish (12 Hz to 14 Hz) or rapid (14 Hz to 16Hz). A pathological spinning pattern is present in widespread encephalopathy, referred to as "spindle-coma".

5. β-(13 Hz to 30Hz): In healthy kids and adults, the β-pulse is the most common. It is most noticeable in the forehead and centre skull areas and gradually fades as it moves backwards. β-activity normally has an amplitude of 10 - 20 μV and rarely exceeds 30 μV. Its amplitude often increases during weariness, and if the N_1 sleeps, it decreases throughout when the N_2 and N_3 sleep. Sedatives, thionyl chloride hydrate, and benzodiazepine, among other sedatives, enhance the amplitude and amount of β-activity in people. A cranial injury, abnormalities, spinal cord compression, epidural, or subgaleal fluid accumulation are all possibilities that can cause focal, regional, or hemispheric suppression of β.

6. HFOs (High-Frequency Oscillations): Vibrational modes with a frequency higher than 30Hz. These are further divided into three categories: gamma (30 Hz to 80 Hz), ripples (80 Hz to 200 Hz), and rapid ripple (200 Hz to 500Hz). Sensation awareness incorporating diverse regions has been linked to the gamma rhythm. HFOs have been the subject of substantial study worldwide, notably in the area of epilepsy. Epileptogenic foci are known for causing high-frequency activity bouts. Ultrafast frequency bursts (fast ripples) have been seen in intracranial depth recordings from epilepsy hippocampal (animal and human models), which are thought to correspond with the localized epileptogenicity of the cerebral cortex. Sub-arachnoid-based space recording during pre-surgical epileptic evaluations, on either hand, has shown that activation outbursts in a lower frequency band (60 Hz to 100 Hz) can also identify the position of an epilepsy focus. Myoclonus HFOs have been identified as prospective biomarkers of the human epileptic cerebral cortex.

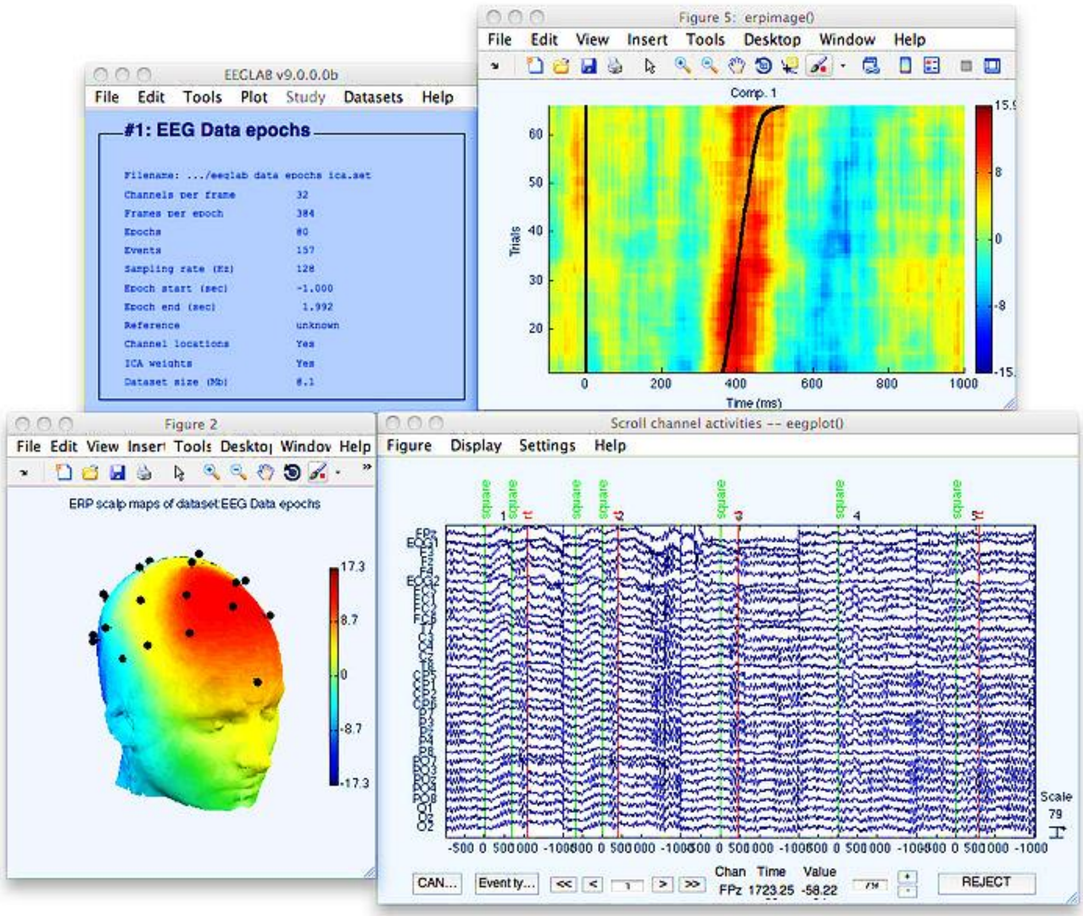

Fig. 1 MATLAB EEGLAB Toolbox

2.3 MATLAB EEGLAB Toolbox

EEGLAB Toolbox from MathWorks is used for analyzing consistent and occasional EEG, Magnetoencephalography (MEG), and other electroencephalographic data. It includes the impartial principle of analyzing the components, time vs frequency analysis, artefact denial, occurrence statistics, and a variety of valuable visualization configurations for an averaged and single feature. Typical EEGLAB Toolbox is illustrated in Fig. 1. EEGLAB uses a graphical user interface (GUI) that allows users to handle high-density EEG and other studies provide insights into the data utilizing autonomous principles analyzing the components and time to frequency analysis (TFA), as well as typical average techniques, flexibly and interactively. To make a move from GUI-based data discovery to batch or custom data supervisory script creation and execution easier, EEGLAB contains extensive instructional and help panels, as well as a command prompt facility. EEGLAB offers several ways to observe and model incidences of significant function at the individual EEGLAB 'data' level and across a group of datasets in an EEGLAB 'study set.' [49].

2.4 Neurosky's' Mindwave EEG headset

The collection of EEG data was carried out using Neurosky's Mindwave EEG headgear equipment which is shown in Fig. 2. It records one EEG signal at a time using parched conductors placed at the prefrontal location (PFL) of the brain, which is referred to as electrodes in the ear lobe. The device, which runs at a minimum of 2.7V and has a frequency of 3 Hz to 100 Hz, uses Thinkgear implementation electronic circuit module dry electrode technology. The silvery TGAM electrodes are suited for use in quasi-regions. The TGAT chip, a sophisticated, completely integrated single-chip EEG sensor, is included in the TGAM. Neurosky's eSense [31], A/D, amplification of skull recognition, and noisy filters for EMG and 50/60Hz AC power-line disturbance are all included in the chip.

Fig. 2 Neurosky MindWave Single-Channel EEG Headset

3. Conventional Machine Learning Algorithms

3.1. Collection of test data using Neurosky's Mindwave EEG headset

During this task, 20 people were asked to close their eyes and keep their brains clear of extraneous ideas. The wearable headset was set up independently for each person, and data was collected for 3 minutes with the eyes closed. The group consisted of both gender from an age group of 25-40 years. The questionnaire prepared for this activity is given in Appendix A. The device's recorded data was transferred to a personal computer using Bluetooth. All data were collected in a room with identical illumination conditions and a calm atmosphere to avoid causing any extra stress. The wavelet decomposition was used to analyze the frequency domain of the EEG data.

The existing EEGLAB dataset was used to train the algorithms used for feature extraction and classification beyond stress and no stress levels. One channel data from the Mindwave headset was acquired and preprocessed using wavelet transform, as shown in Fig. 3, with the help of the questionnaire. Generating the dataset of these 20 people is one of the contributions of this research activity.

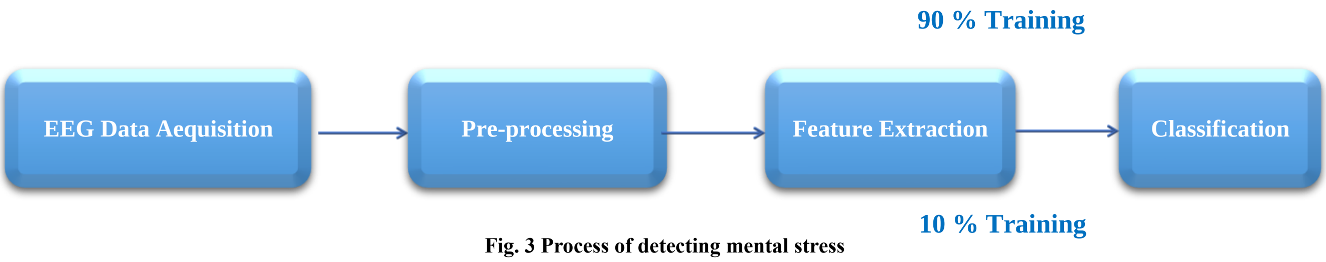

Fig. 3 Process of detecting mental stress

The dataset available with the EEGLAB toolbox is shown in Fig. 4.

Channels per frame	32
Frames per epoch	30504
Epochs	1
Events	154
Sampling rate (Hz)	128
Epoch start (sec)	0.000
Epoch end (sec)	238.305
Reference	unknown
Channel locations	Yes
ICA weights	No
Dataset size (Mb)	4.3

Fig. 4 EEGLAB Toolbox

A 32-channel brain-computer interface is used for data acquisition in the existing dataset of EEGLAB. The acquired waveforms for one subject are shown in Fig. 5. A graph of spectral power at different frequencies and channel one data for its spectral power is shown in Fig. 6 and Fig. 7, respectively.

It can be seen from Fig. 6 that the signal has a peak frequency of 8 Hz, indicating a relaxed state of mind.

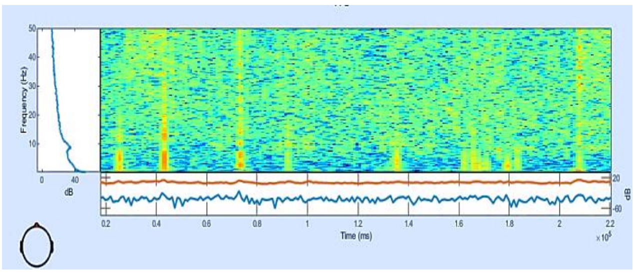

Fig. 5 EEG Signal at Channel 1

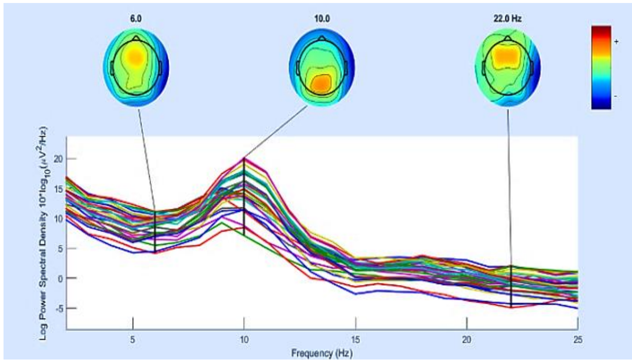

Fig. 6 Spectral Power at different frequencies

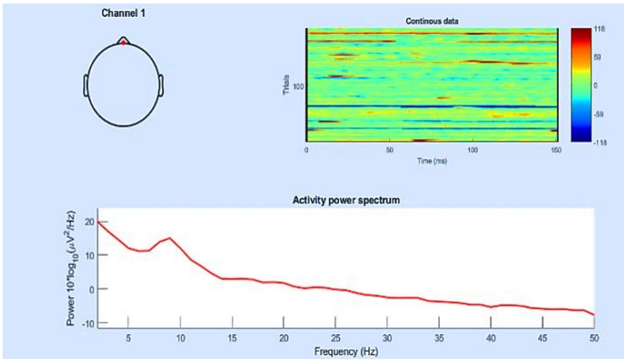

Fig. 7 Channel 1 data and its power spectrum concerning frequency

3.2. Deployment of Conventional Algorithms for Stress Detection

3.2.1 SVM Algorithm for Stress Detection

SVM is a supervised learning technique that can be applied to various classification and regression problems, including signal processing, computational linguistics, and audio and image identification. The SVMs' purpose is to generate a hyperplane that separates data from one category from another class to the maximum extent possible. In the diagram below, "best" is defined as the high energy with the greatest disparity between the 2 categories, as shown by the small deviation in Fig. 8. The total width of the surface is orthogonal to the hyper-plane with no inside data points is called the margin. The approach can only locate such a hyper-plane for linearly separable issues; for most actual situations, the algorithm optimizes the slender edge, permitting a relatively tiny group of errors.

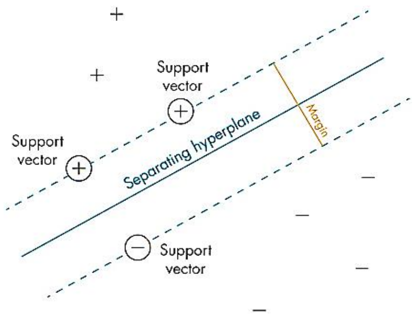

Fig. 8 Establishing the "margin" across subclasses, which is the criterion that SVMs are trying to improve

Attribute values are a subtype of preparatory stages that specify where the dividing hyperplane should be placed. Multiclass issues are often simplified to a string of binary situations, and the standard SVM technique is developed for binary classification. In this research work, SVM is used to classify the EEG signals in mental stress or relaxed state according to the flowchart given in Fig. 9. The frequency bands form features of the classifier.

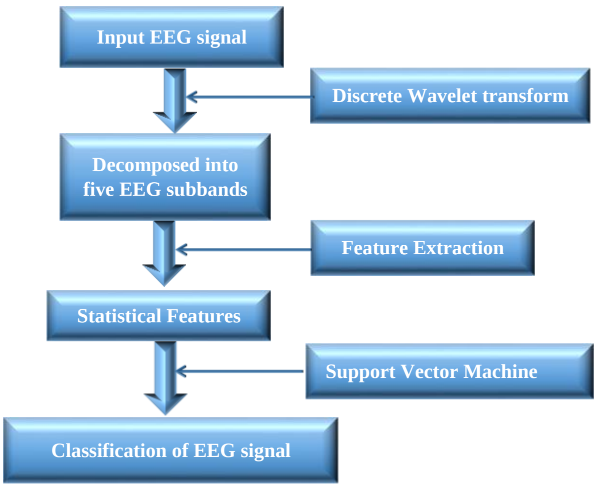

Fig. 9 Flowchart for SVM-based mental stress detection

3.2.2. RNN Algorithm

The RNN is indeed a supervised neural network arrangement that enhances the show's efficiency on present and time-ahead signals by using knowledge from the previous. The existence of a hidden layer and loop distinguishes RNNs. The cyclical structure of the network allows it to store past data on a hidden layer and act on sequences. Because of these characteristics, recurrent neural networks are highly suited to handling several issues involving sequential data of various durations, such as:

- Signal classification,
- Video analysis, and
- Natural language processing [49].

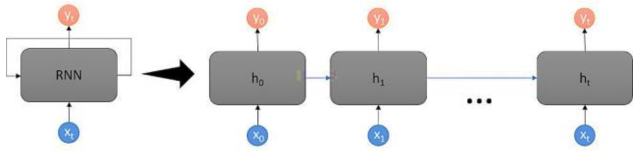

Fig. 10 An RNN cell is unrolled one at a time.

Fig. 10 depicts how a data sequence moves via the system. The hidden layer of the cellular unit acts on the elements to generate the outcome, and the hidden layer is transmitted to another sampling interval. There are 2 types of network weights: one for obscured vector field and the other for the output results. This network can learn the weight for input and the hidden layer throughout activation. The outcome is based on the current intake and the hidden layer, dependent on prior input when enabled. The training algorithm is a typical method for training RNNs, and it can result in either a vanishing or an expanding gradient issue. The networking values sometimes become extremely low or very high due to these issues, reducing the efficacy of establishing carriage returns. In this study, RNN is used to identify stress similarly to SVM.

3.2.3. LSTM Networks

Lengthy correlations among clock cycles of data sets may be learned using an LSTM model. A pattern-based input layer and an LSTM layer are the two main components of an LSTM network. A sequential input layer feeds packets into the system in the form of a sequence or a time series. The long-term relationships among sequence data time steps are learnt using an LSTM layer. Fig. 11 shows the construction of a simple LSTM network for assessment. A sequence input phase is defined by either an LSTM intermediate node. The network finishes with a convolution layer, a soft-max layer, and a segmentation output vector to forecast classifier.

Establish a layered array with sequences of input nodes, an LSTM surface, a fully-connected layers, a Soft-max, and a categorization output unit to make an LSTM network for sequential classifications. Set the number of features inside this input data to the size of the serial input layer. Make the completely linked layer the same size as the class labels. Fig. 12 shows the transport for time-series data X containing C characteristics (streams) of dimensions S via LSTM layers.

Fig. 11 LSTM Network Architecture

The consequences (also described as that of the hidden state) and the transceiver at time interval t are represented in the diagram by h_t and c_t, respectively.

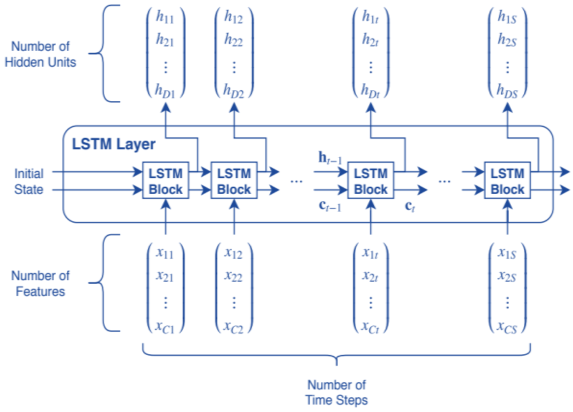

Fig. 12 LSTM Layer Architecture

The first LSTM block computes the first result and the modified corresponding output using the initial condition of the network and sequence's 1st phase. Using the current network state (c_{t-1}, h_{t-1}) then, the next periodic stride in the sequence, the module computes the outcome and the modified corresponding output c_t at sample time t.

The concealed information (commonly known as the output state), as well as the layer of the network, make up the layer's state. The outcome of the LSTM layer for such a sampling interval is stored in the hidden neuron at time step t. The preceding time steps' data is contained in the cell state. The layer includes or subtracts data from the cell state at every sampling interval. Furthermore, the layer includes or subtracts data from the cell state. The layer uses gates to regulate these changes. This image depicts the flow of information at intervals t. The diagram in Fig. 13 depicts how the gating remembers, modifies, and emits the hidden and cellular states.

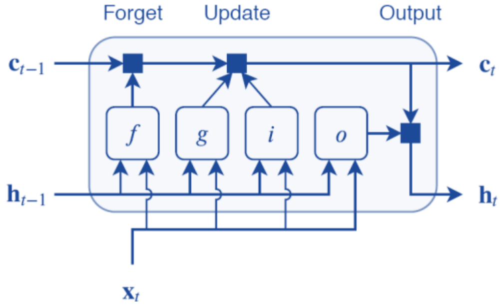

Fig. 13 Gates of LSTM Layer

4. Proposed RNN-LSTM Algorithm

4.1. Proposed Method of LSTM-RNN for Mental Stress Detection

The construction of a basic LSTM network for regression is shown in Fig. 14. Sequential layers of inputs are fed to LSTM, which is further fully connected, and the output response is regressive.

To develop an LSTM model for sequential forecasting, a multi-arrangement with a pattern artificial neuron, an LSTM layer, fully linked layers, and a regress output unit is introduced. A variety of features (EEG Frequency Bands) are set inside the data input to a length of the sequential input nodes. A completely linked level the same size as the number of responses is thus made. The proposed parallel fusion RNN-LSTM method is depicted in Fig. 15 as a flowchart.

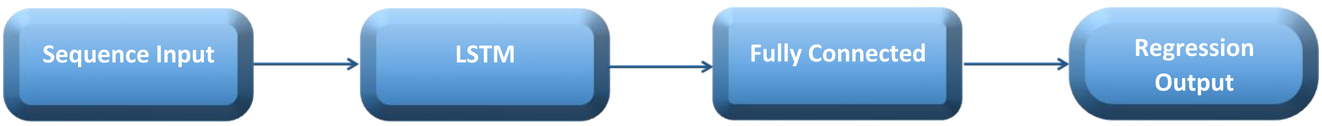

Fig. 14 a) RNN-LSTM Output

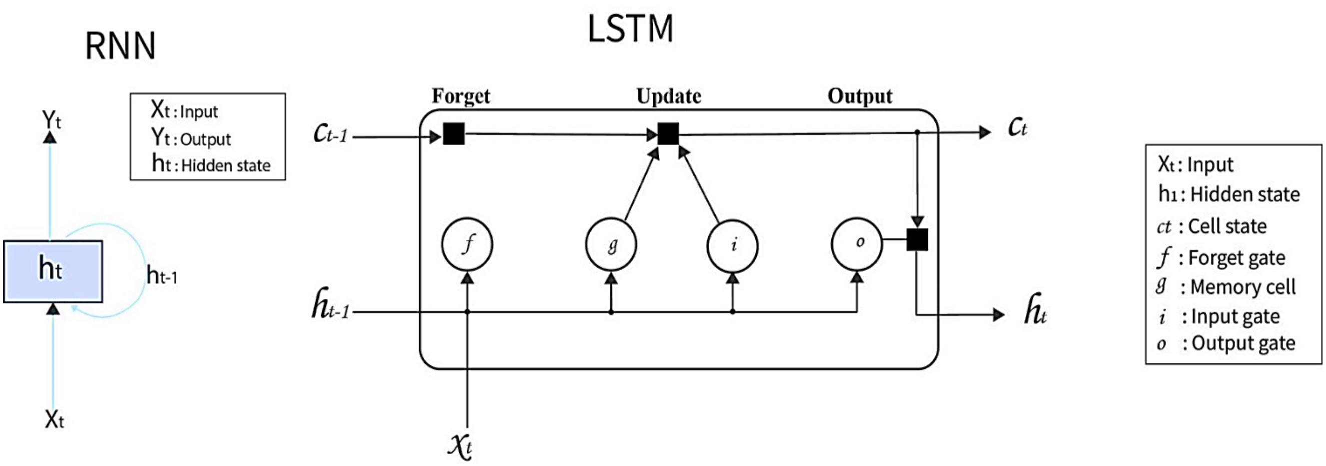

Fig. 14 b) RNN-LSTM Network layer

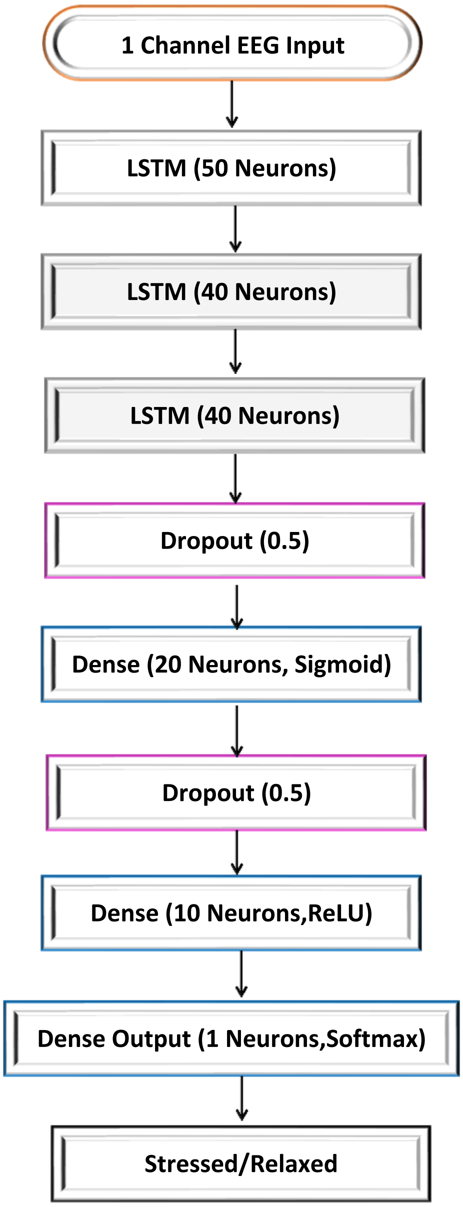

Fig. 15 Flowchart for LSTM with dropout layer

LSTMs can selectively recall similarities for just a significant period, which is important for extracting features from physiological data. RNN, on the other hand, can quickly discern the recurrence of patterns in a signal. To minimize over-training of sequence data from LSTM, the proposed technique follows each fully - connected with a 0.5 single hidden layer that discards 50% of random features.

This data and information utilize RNN, and then after dropping, the final FC layer is linked to the categorization hidden layers through to the softmax for LSTM condition categorization. This technique is novel and is one of the contributions of this research work. A 50% reduction in random features reduces the data size to be handled, and conjunction for two classifiers increases the accuracy of the results. It can be seen from Fig. 16 that after the feature extraction step, RNN continues to sample the values; however, LSTM starts the classification process parallelly.

4.1. Training existing dataset from EEGLAB Toolbox

The EEGLAB dataset consists of 32 channels from a brain-computer interface. Only channel 1 input is considered for training purposes, as shown in Fig. 17. Data from 10 EEG signal sources are used to train the algorithms. Before training, data preprocessing, decomposition and feature extraction are done using wavelet transformation. The data from single-channel and its decomposition to different EEG frequency bands are shown in Fig. 18.

The EEG signals are converted to frequency and time domain signals using the Parks-McClellan optimal equiripple finite impulse response order estimator and a Chewing function in MATLAB, a Chebyshev filter. The spectrum of filtered outputs is shown in Fig. 19.

These features are used for classifiers as input for the algorithm's training. The weights used for training are decided based on the average values of the training dataset for all frequency bands' power spectrums.

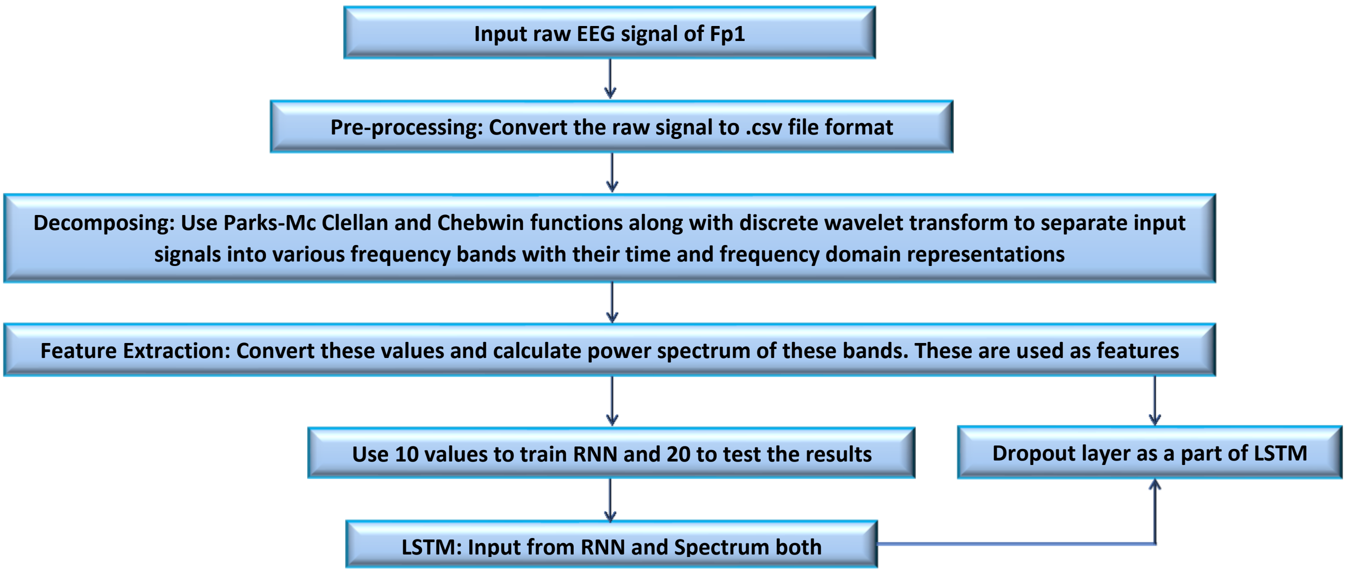

Fig. 16 The flowchart of the proposed RNN-LSTM combined for mental stress detection

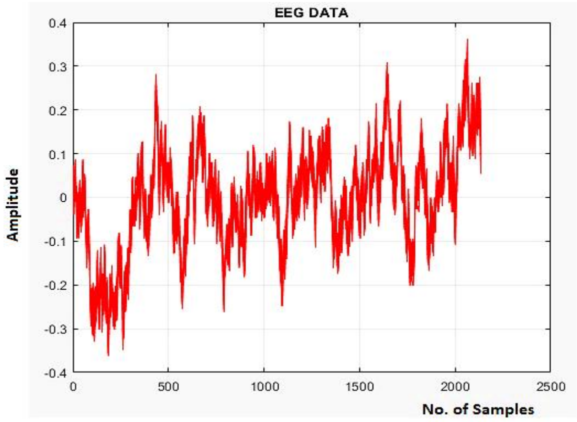

Fig. 17 EEG Signal from a stressed mind

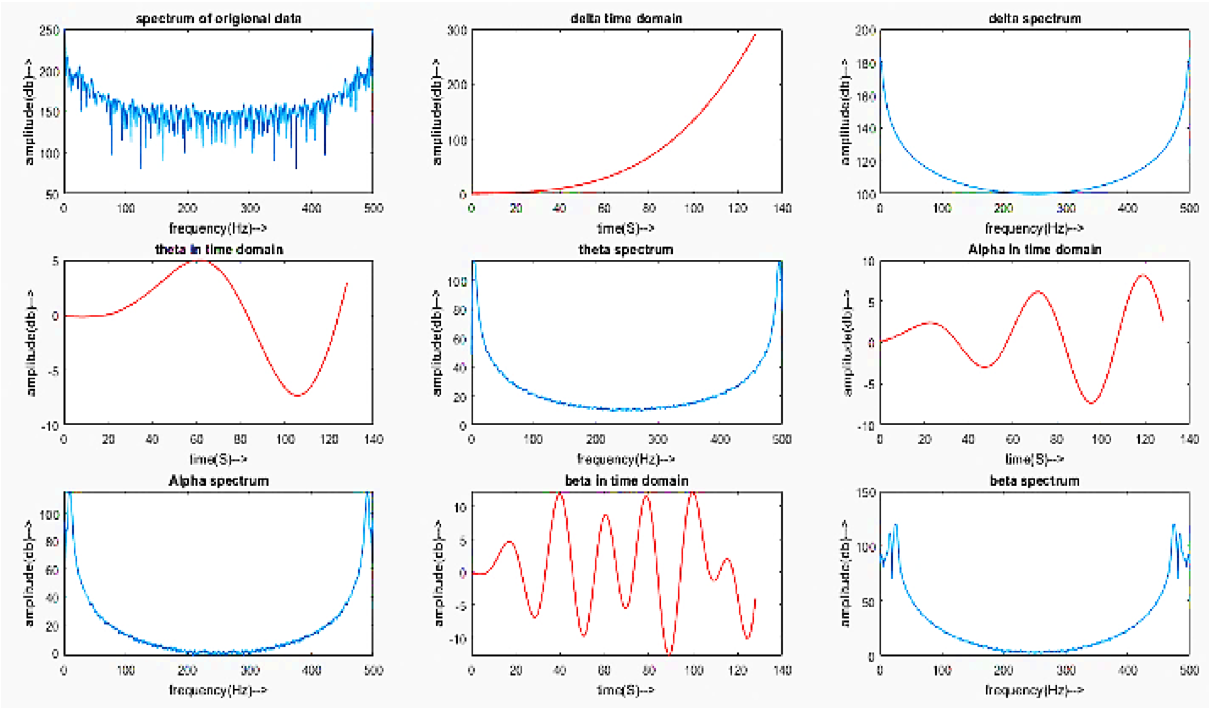

Fig. 18 Decomposition of EEG signals in different frequency bands

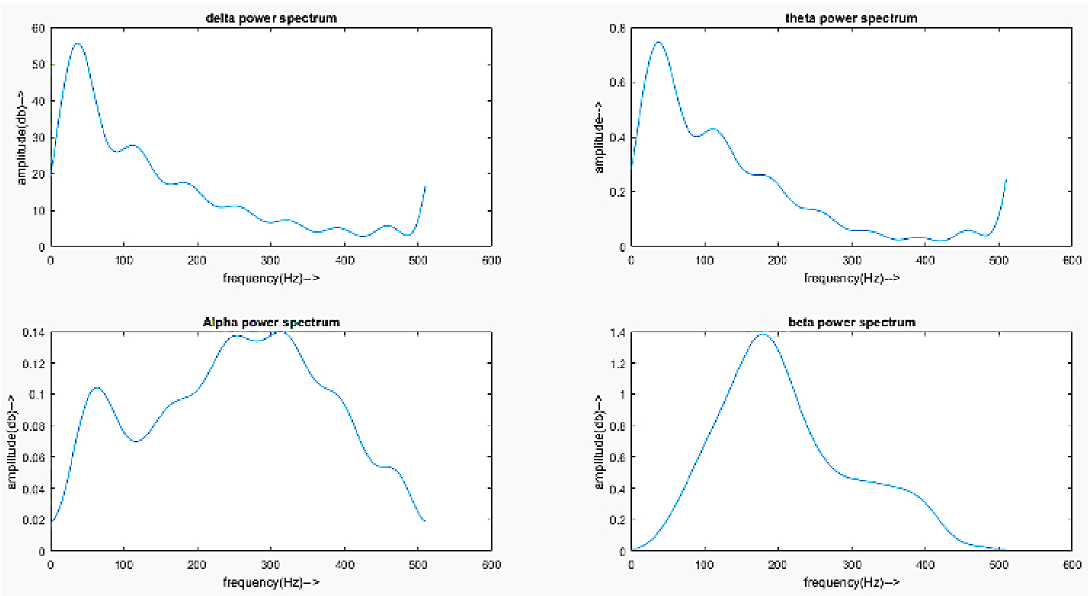

Fig. 19 Power Spectrum of different EEG frequency bands used as features

4.2. *Testing of the dataset created*

The authors collaborated with Dr. Rajesh Alone, a Sigmund Freud's Mental Health Research & Psychoanalysis Institute psychologist, to verify the people's state of mind based on samples given to him. The physician assessed the EEG signals gathered from the individual as stressed or calm, as indicated in Table I.

Table 1. Evaluation of Mental Stress by Doctor

Patient No.	State of Mind
1	Stressed
2	Stressed
3	Relaxed
4	Relaxed
5	Relaxed
6	Stressed
7	Relaxed
8	Stressed
9	Relaxed
10	Relaxed
11	Stressed
12	Stressed
13	Stressed
14	Stressed
15	Relaxed
16	Stressed
17	Relaxed
18	Relaxed
19	Stressed
20	Stressed

MATLAB-based algorithms were used to run the experiments. The information regarding detecting the mental state from EEG and psychological and physiological data was taught to the algorithms using 10 indicators from the available data. Around 33% of the data was used for training, while the remaining 67% was used to test the efficacy of the algorithms.

5. Results and Discussions

5.1. *Results of the Proposed Classifier*

The accuracy of different algorithms used in this research work is shown in the form of a bar chart in Fig. 20. It can be seen from the figure that the proposed parallel fusion RNN-LSTM algorithm gives the highest accuracy among the compared algorithms. The findings, which show that RNN - LSTM categorizing is more precise than other machine learning techniques, emphasize the importance of EEG data for stress evaluation using RNN - LSTM classifications. The findings, which show that RNN - LSTM categorization is more effective than some other machine learning techniques, emphasize the importance of EEG data for stress evaluation using RNN - LSTM categorizing. An improvement of at least 5% to 15% is seen in the test results, as shown in Fig. 21 and Fig. 22.

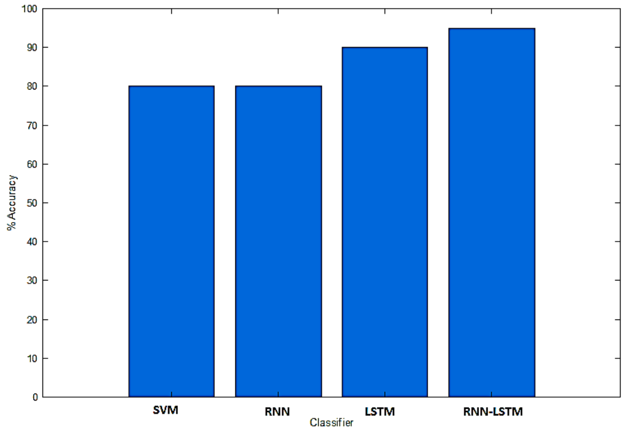

Fig. 20 Percentage Accuracy of Classifiers for created dataset

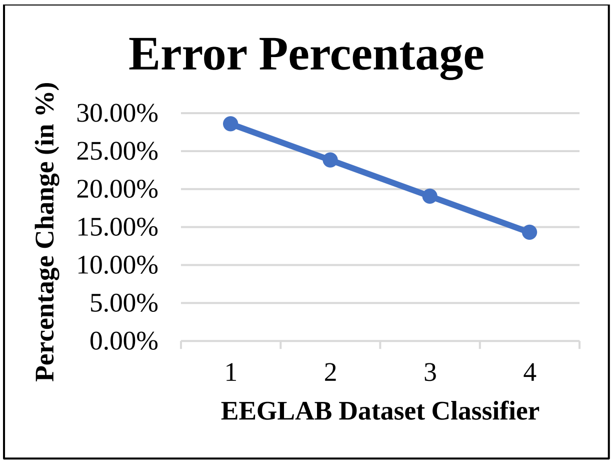

Fig. 21 Change in percentage error of SVM, RNN, LSTM and proposed RNN-LSTM of EEGLAB Dataset Classifier

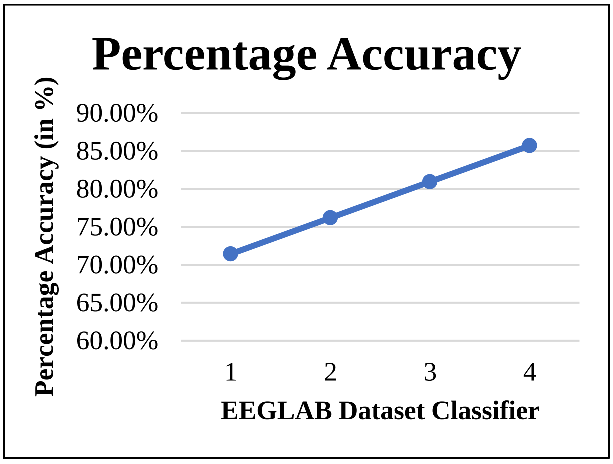

Fig. 22 Percentage accuracy of SVM, RNN, LSTM and proposed RNN-LSTM of EEGLAB Dataset Classifier

5.2. *Testing the algorithms on DEAP Dataset*

The development of the algorithm is tested using DEAP Dataset in "DEAP: A Database for Emotion Analysis using Physiological Signals (PDF) written by S. Koelstra, C. Muehl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, I. Patras in EEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18-31, 2012" [50]. The algorithms are tested on 21 subjects from the dataset, which classify emotions into happy and angry categories. For this research, the happy state of mind is converted to a relaxed state and the angry state is converted into a stressed state. In the dataset, there were 12 angry participants and 9 happy participants. The same EEGLAB dataset was used to train the algorithms.

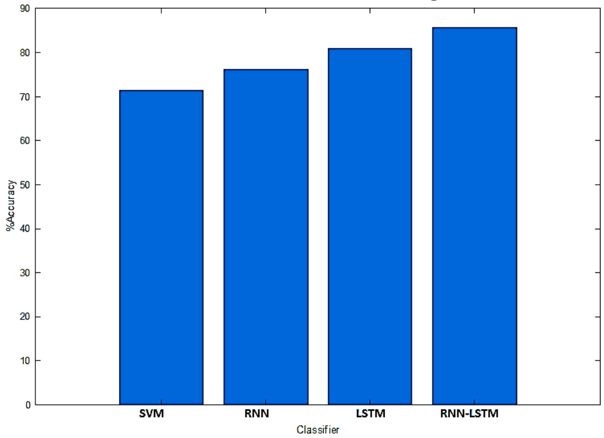

Fig. 23 Percentage Accuracy of classifiers for the DEAP dataset

The response of the proposed RNN-LSTM is shown in Fig. 23, which gives better results than other algorithms. Moreover, it was observed that the time taken to simulate the results due to the dropout layer was reduced to 9.83 secs from twice that in the RNN-LSTM algorithm.

6. Conclusion and Future Directions

EEG signals from a person's mind can be used to identify many sorts of emotions. The EEGLAB toolbox's dataset of 10 EEG signals was utilized for training the machine learning algorithms. Using a Neurosky Mindwave EEG headset, an EEG dataset of 20 patients from a well-known psychologist was obtained. To separate the signals into different frequency bands. To categorize the state of mind, an RNN-LSTM-based classifier was suggested and evaluated against existing classifiers, including SVM, RNN, and LSTM. It was demonstrated that the recommended approach had an accuracy of 5% to 15% greater than previous methods.

Additionally, the DEAP dataset was utilized to evaluate classifier accuracy for further validation of results, showing that the new approach performs better than earlier techniques. The goal of this research's future work is to evaluate a suggested algorithm for stress detection using voice signals. To design a novel algorithm for stress identification utilizing EEG and above signals and evaluate a suggested method for detecting stress using audio-visual inputs. The developed algorithm is recommended for further evaluation and use in a practical scientific environment like research laboratories and medical institutes.

Appendix A

Questionnaire for Dataset formation

The answer is as minimum words as possible or a simple yes/no.

1. What is your name?
2. What is your profession?
3. Did you sleep well last night?
4. Do you feel you are leading a successful life?
5. Do you have conflicts with anyone?
6. Were you happy as a child?
7. Do you feel stressed at work?
8. Do you feel you have a healthy work-life balance?
9. Do you have a good family life?
10. Do you feel you are stressed right now?

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