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Fusion of RNN and LSTM for the Identification of Mental Stress in EEG Signal

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Abstract: Proficiently managing stress and recognising it promptly are crucial for facilitating recuperation and averting additional difficulties. Traditional techniques for evaluating anxiety—such as interviews, stress-related enquiries to understand an individual's mental condition, and the analysis of facial expressions including eyebrow movement, pupil dilation, or rapid eye blinking—exhibit limitations and may not encompass all manifestations of stress. The electroencephalogram (EEG), a contemporary physiological method, demonstrates potential as an effective instrument for detecting stress in daily environments, attributed to the increasing availability and cost-effectiveness of commercial EEG headsets. This research utilised machine learning methodologies to categorise stress levels derived from resting-state EEG data. Data was obtained from the MathWorks® EEGLAB toolkit and a custom dataset of 20 participants, assembled through surveys and measurements from the Neurosky Mindwave EEG headset. Stress classification was conducted utilising support vector machines (SVM), recurrent neural networks (RNN), long short-term memory (LSTM) networks, and an innovative hybrid approach integrating RNN and LSTM into a parallel fusion model. MATLAB simulation results demonstrate that the suggested method is superior in speed and accuracy compared to other machine learning models, with a 95% accuracy rate—reflecting an improvement of up to 15% over prior methodologies.

Index Terms: Stress detection, EEG signals, machine learning, EEGLAB toolbox, Meurosky's Mindwave EEG headset, MATLAB.

I. INTRODUCTION

Mental stress, a psychological phenomena that reflects the body's intrinsic defences against predators and danger, has been more prevalent in recent years due to its prominence as the most important societal issue of the twenty-first century, particularly during the Covid-19 epidemic [1-4]. It is vital to diagnose mental stress early on. It is vital to recognise mental stress early on to avoid any serious health consequences owing to it [5]. Stress may be detected and quantified using a range of techniques and procedures, including Positron Emission Tomography (PET), electrocardiogram (ECG), Electromyography (EMG), and magnetic resonance imaging (MRI) [6], [7]. EEG is a medical method that measures the physiological aspects created by electrical activity in the brain [8], [9]. EEG is the finest alternative over ECG, EMG, PET, and Functional magnetic resonance imaging for faster, less expensive, and much more approachable insight into brain activities and high time resolution. EEG has become a significant tool since it is based on a non-invasive technology that employs stress hormones as input, allowing it to be utilized as an accurate and trustworthy instrument for stress computation in cognitive and neuroscience research [10]. With the application of a breakthrough machine-learning algorithm, mental tension is recognized using EEG data in this study.

Stress is described as a state of intense pressure and mental strain in layman's words., however it is defined in scientific studies as a bodily process that responds to a challenge or a body reaction to mental, emotional, or physical pain [11-12]. The fight-or-flight response is the moniker for this system. It also partially or totally effects the practicality of ordinary labour and the country's economy [13].

Because there is limited opportunity to recuperate between trials, stress might produce mental and behavioural changes [14], [15]. These variations represent stress symptoms. Perspiration, spasms, dizziness, migraines, hypertension, muscular pains, and night terrors are all common symptoms; problems are examples of somatic symptoms, whereas psychological symptoms include wrath, anxiousness, despair, memory confusion, mood swings, and melancholy [16-17].

Food cravings, unexpected furious outbursts, more cigarette or alcohol usage, and frequent tears have all been recognized as key stress symptoms in stressed persons [18]. Stress could not only generate dysfunctional conduct, but it can also increase hypertension, cardiovascular illness, and gastrointestinal disease if it lasts for a long time [19-20].

As a result, researchers must notice tension at a preliminary phase, and individuals must be aware of the implications of being over-stressed before it produces serious health concerns [21–23].

Stress damages human health and weakens the immune system [24–26]. As a result, the scientific community is focussing on establishing the best approach for recognizing stress early on to prevent it from becoming chronic and giving remedies to avoid irreparable injury [27–30]. To serve society, low-cost, precise, and efficient technology for emotion recognition and mitigation measures are needed in healthcare, educational, scientific, military, science, athletics, or social activities are some of the sectors where the government and industry intersect [31].

Various methods for assessing and researching stress levels have been devised, including questionnaires, examinations, and surveillance of people to measure changes in physiological signals [32–34]. Physiological signals can be captured and analysed with better precision in online real-world applications for the evaluation of anxiety, which may be separated into two subgroups:

- "Invasive type" and
- "Non-invasive form" [35].

Invasive therapies have drawbacks in some operations, such as testosterone analysis, leading the development of non-invasive, efficient, exact, and trustworthy technologies [36]. The following approaches, which may diagnose stress using individual physiological data, are considered as non-invasive procedures [37–40]. EEG is the ideal choice above other non-invasive technologies for faster, cheaper, and more accessible insights into brain processes with a tight temporal resolution [41–44]. Small metal discs with thin wire electrodes are implanted on the scalp, and impulses are transmitted to a device that records the information [45]. Due to the rapid nature of these electrical changes, exact temporal precision on the microsecond level may be attained [46]. The graphs of the brain's electrical energy vs time are mentioned in [47-48].

In this work, mental stress is recognised using EEG signals utilising a parallel fusion RNN-LSTM-based innovative machine learning approach. Conventional machine learning algorithms like SVM, RNN, and LSTM are compared with the suggested approach 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 developed using Neurosky's Mindwave EEG headset on sample patients. The recommended method looks to outperform established algorithms, according to the data.

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

II. EEG SIGNALS

A. *EEG Features*

EEG activity is a temporal summation of the synchronized activity of millions of finely coordinated brain cells. EEG analysis and interpretation are both an art and a science. The usual EEG has a wide range of physiological variability and is fairly varied. When examining the waveforms in an EEG recording, it's vital to employ a systematic methodology. Even before commencing the analysis, one needs know multiple confounding factors, including as the patient's age, level of awareness, the existence of muscular function, and the presence of various biological, ecological, and pharmaceutical medications that may alter the waveforms. The position, size, duration, structure, consistency (periodic, random, or consistent), synchronization, symmetry, and responsiveness of EEG waves may all be used to characterise them. ð (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 conventional spectrum of clinical EEG, such as ultra-slow oscillation (less than 0.5 Hz) and raised oscillations (greater than 30 Hz), have suddenly acquired clinical importance with the rise of digital signal analysis.

B. *Measurement of Frequency*

The usual spectrum of industrial EEG concentrates on pulses with wavelengths ranging from 0.5-70 Hz. The EEG recordings are subjected to frequently associated filtering for this study. A bigger EEG gamut, albeit at the other extreme, has been explored by medical groups and academics and has been found clinically important in specific conditions. When the infra-slow or ultra-fast regions of the frequency range are deleted from normal EEG, several physiological and pathologically relevant aspects of cerebrum activity are lost. A full-bandwidth EEG (FbEEG) evaluates all physiologically and therapeutically significant waveforms without making any concessions that favour one frequency range over another. Conversely, collecting EEG data at extremely high frequencies is not typical in clinical practice since it requires specialist equipment to obtain data with greater sampling rates, tripling the amount of storage space necessary.

EEG waveforms may be divided into numerous sorts based on the FbEEG recording: - Intradural oscillation (ISO) (just about 0.5 Hz): ISOs are actually the dominating frequency in preterm babies, and they range from 0.01 Hz to 0.1 Hz. It is also known as spontaneously activity transients (SAT). It is endogenous cannabis driven, spontaneously activities that are crucial in building brain connections at such an early infancy period when sensory input is low. Furthermore, during non-REM sleep, ISOs across the 0.02 to 0.2 Hz frequency range are found, phase synchronised with high frequencies EEG activity.

The majority of low-frequency EEG research has focused on conditional activation caused negative variability, motor motions, and the orienting paradigm. The amplitude of these sluggish scalp-recorded potentials is typically only a few microvolts, necessitating Fb-EEG- based electrodes and skin-based electrode connections for real DC-type features for accurate audio-based recording. Furthermore, spasms are associated with relatively sluggish EEG reflexes 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 have indicated that localized onset episodes are associated with persistent and relatively substantial DC alterations.

1) ð- within the range of 0.5 Hz to 4 Hz: ð-rhythm is physiologically perceptible in profound slumber and is prevalent in nearly identical head positions. A broken rhythm arises in waking states in cases of severe neurodegeneration and targeted neurodegeneration. Adults have frontal intermittent rhythmic ð-activity, whereas the children's occipital rhythm is uncommon. Patients with status epilepticus frequently experience temporal interspersed rhythm ð activity (TIRDA).
2) θ- within the range of 4 Hz –7 Hz: This is the cadence that is set off by tiredness in the early stages of sleep, such as N1 and N2. Linked to early tiredness, it is most apparent in the inferior frontal brain zones and gradually makes its way rearward, replacing the α-cluster. In kids and early adults, higher emotional moods can also increase prefrontal cyclic θ rhythm. During awake phases, localized θ The existence of activity is a symptom of regional brain dysfunction.
3) α-(8–12Hz): In typical awake EEG recordings in the frontal head area, the dominating anterior groove is often evident. It is the distinguishing constituent of the adult EEG recording's regular ambient frequency. In healthy adults, 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 versions of the atmospheric beat have been observed among the general populace. The backstory's decrease is viewed as a sign of severe brain injury. The rhythms fluctuate from patient to patient and from time to time within such a single individual. The - rhythm's responsiveness is a distinctive quality that aids in its identification. It is most noticeable when the eyes are open, the mind is relaxed, and it is typically lessened when the eyes are opened and mental effort is exerted. Patients with broad encephalopathy may have generalized -activity, which is non-responsive to internal stimuli and is known as “ -coma”. -rhythm is a form of -rhythm with an arch-like architecture that arises in the central head regions. This pattern often terminates with contralateral limb motor action or contemplation about initiating the motor activity. Eye-opening, on the other hand, is mostly unaffected. Young individuals are the most typically afflicted, whilst adults and children are less affected. Insomnia, sensorimotor stimulation, and mathematical aptitude are all variables that diminish the effectiveness of the treatment. On both ends, they are highly uneven and erratic.
4) Waves: sleep patterns, also known as Œ-waves, are a sort of activity that happens medically during N2 sleep. They are mainly evident in the fronto-central head areas and could be sluggish (12 Hz to 14 Hz) or fast (14 Hz to 16Hz). A pathological spinning pattern is observed in widespread encephalopathy, referred to as “spindle-coma”.
5) (13 Hz to 30Hz): In healthy kids and adults, the - pulse is the most prevalent. It is most evident in the forehead and central skull areas and gradually disappears as it advances backwards. -activity generally has an amplitude of 10 - 20 8and seldom surpasses 30 8. Its amplitude generally increases with weariness, and if the N1 sleeps, it lowers throughout when the N2 and N3 sleep. Sedatives, thionyl chloride hydrate, and benzodiazepine, among other sedatives, boost the amplitude and amount of -activity in humans. A cranial injury, anomalies, spinal cord compression, epidural, or subgaleal fluid accumulation are all causes that can induce localised, regional, or hemispheric suppression of .
6) HFOs (High-Frequency Oscillations): Vibrational modes having a frequency higher than 30Hz. These are further separated into three categories: gamma (30 Hz to 80 Hz), ripples (80 Hz to 200 Hz), and rapid ripple (200 Hz to 500Hz). Sensation awareness including multiple regions has been connected to the gamma rhythm. HFOs have been the focus of extensive investigation globally, notably in the domain of epilepsy. Epileptogenic foci are recognised for creating high- frequency activity episodes. Ultrafast frequency bursts (fast ripples) have been found in intracranial depth recordings from epileptic hippocampus (animal and human models), which are assumed to coincide with the localized epileptogenicity of the cerebral cortex. Sub-arachnoid-based space recording during pre- surgery epileptic assessments, on either hand, has revealed that activation outbursts in a lower frequency band (60 Hz to 100 Hz) can also detect the place of an epilepsy focus. Myoclonus HFOs have been identified as potential biomarkers of the human epileptic cerebral cortex.

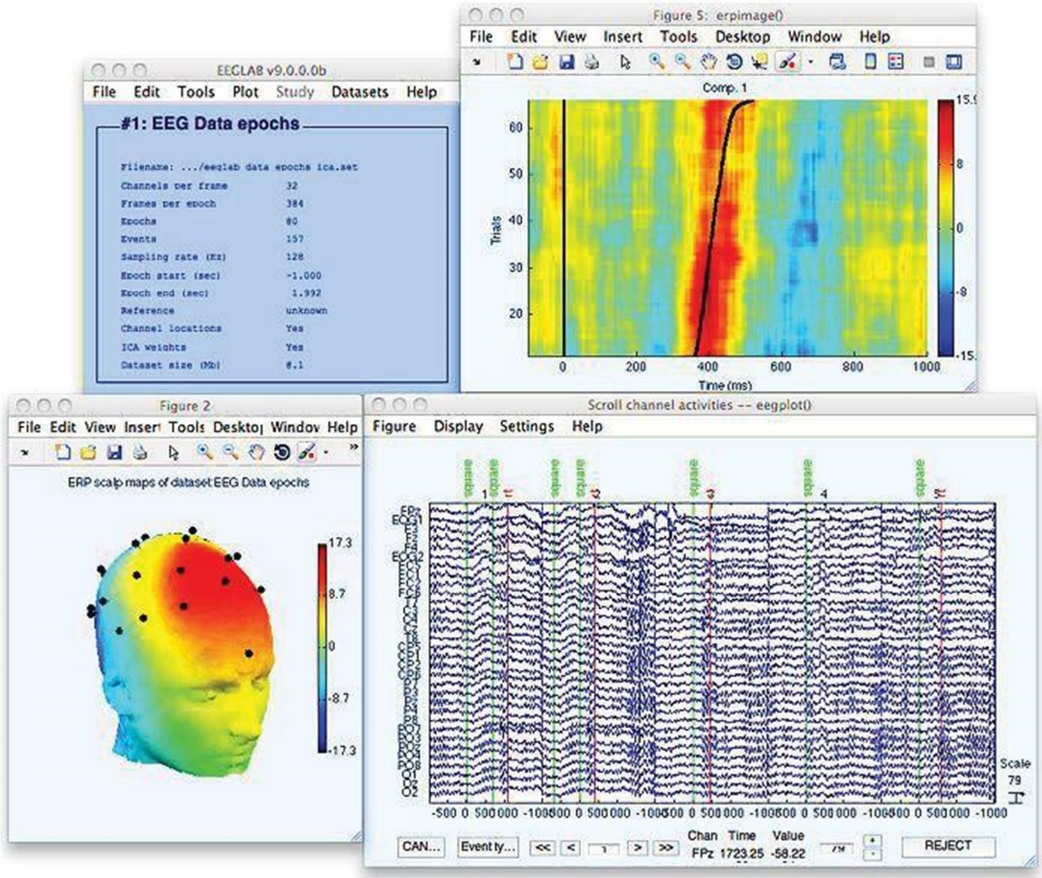

Fig. 1 MATLAB EEGLAB Toolbox

C. MATLAB EEGLAB Toolbox

MathWorks' EEGLAB Toolbox analyses EEG, Magnetoencephalography (MEG), and other electroencephalographic data, both consistently and sometimes. It incorporates the unbiased principle of studying the components, time vs frequency analysis, artefact denial, occurrence statistics, and a range of helpful display configurations for an averaged and single feature. Typical EEGLAB Toolbox is displayed in Fig. 1. EEGLAB employs a graphical user interface (GUI) that enables users to manage high-density EEG and other studies that provide insights into the data by utilising autonomous principles analysing the components and time to frequency analysis (TFA), as well as traditional average techniques, in a flexible and interactive fashion. To make a switch from GUI- based data discovery to batch or bespoke data supervision script generation and execution easier, EEGLAB offers extensive instructional and help panels, as well as a command prompt facility. EEGLAB offers numerous techniques to monitor and model instances of important function at the individual EEGLAB 'data' level and across a group of datasets in an EEGLAB 'research set.' [49].

D. Neurosky's' Mindwave EEG headset

The collection of EEG data was done out utilising Neurosky's Mindwave EEG headgear equipment which is depicted in Fig. 2. It records one EEG signal at a time utilising two conductors inserted at the prefrontal location (PFL) of the brain, which is referred to as electrodes in the ear lobe. The gadget employs Thinkgear implementation electronic circuit module dry electrode technology and operates at a minimum voltage of 2.7V with a frequency ranging from 3 Hz to 100 Hz. The silvery TGAM electrodes are appropriate for application in quasi-regions. The TGAT chip, a powerful, completely integrated single-chip EEG sensor, is featured in the TGAM. Neurosky's eSense [31], A/D, amplification of skull recognition, and noise filters for EMG and 50/60Hz AC power-line disruption are all integrated in the chip.

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Fig. 2 Neurosky MindWave Single-Channel EEG Headset

III. CONVENTIONAL MACHINE LEARNING ALGORITHMS

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

During this task, 20 participants were requested to close their eyes and keep their brains clear of unnecessary notions. The wearable headset was set up independently for each subject, and data was recorded for 3 minutes with the eyes closed. The group consisted of both gender from an age bracket of 25-40 years. The questionnaire produced for this activity is presented in Appendix A. The device's captured data was sent to a personal computer using Bluetooth. All data were taken in a room with identical illumination conditions and a peaceful ambiance to prevent producing any extra stress. The wavelet decomposition was utilised to investigate the frequency domain of the EEG data.

The current EEGLAB dataset was used to train the algorithms used for feature extraction and categorisation beyond stress and no stress levels. The questionnaire assisted in the acquisition and preprocessing of one channel data from the Mindwave headset using wavelet transform, as seen in Fig. 3. Generating the dataset of these 20 people is one of the contributions of this research endeavour.

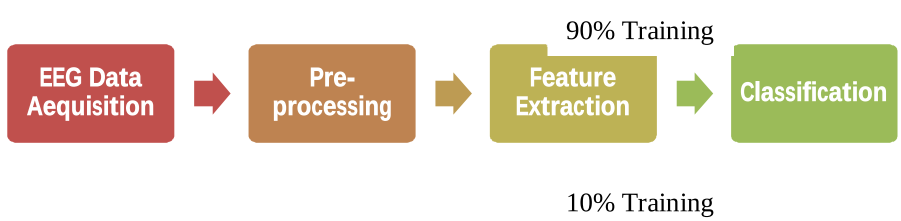

Fig. 3 Process of detecting mental

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.

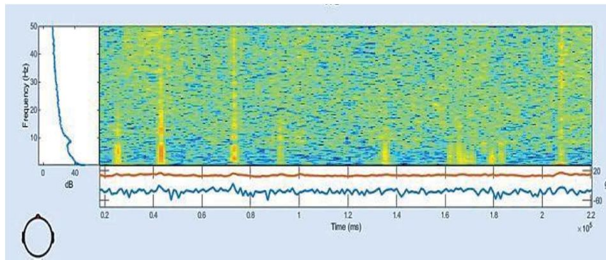

Fig. 5 EEG Signal at Channel 1

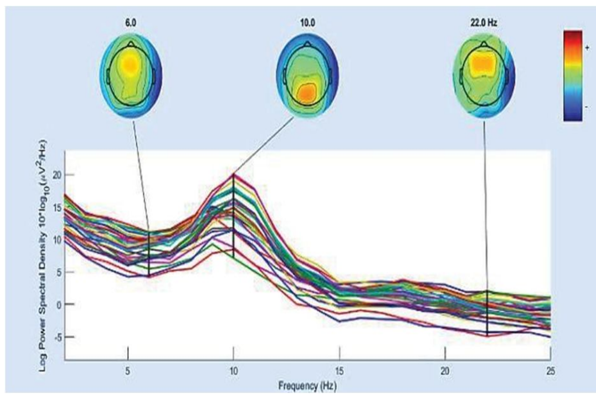

Fig. 6 Spectral Power at different frequencies

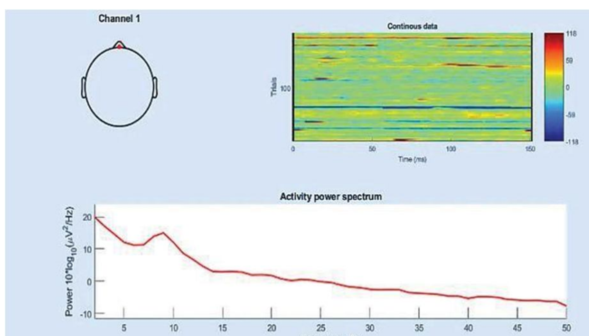

Fig. 7 Channel 1 data and its power spectrum concerning frequency

B. Deployment of Conventional Algorithms for Stress Detection

1) SVM Algorithm for Stress Detection

SVM is a supervised learning approach that may be used to numerous classification and regression difficulties, including signal processing, computational linguistics, and audio and picture recognition. The SVMs' purpose is to generate a hyperplane that separates data from one category from another class to the fullest extent feasible. In the figure below, “best” is defined as the high energy with the largest divergence between the 2 categories, as indicated by the minor deviation in Fig. 8. The whole breadth of the surface is orthogonal to the hyper-plane with no inside data points is termed the margin. The technique can only discover such a hyper-plane for linearly separable concerns; for most real occurrences, the program optimizes the narrow edge, enabling a very minor group of mistakes.

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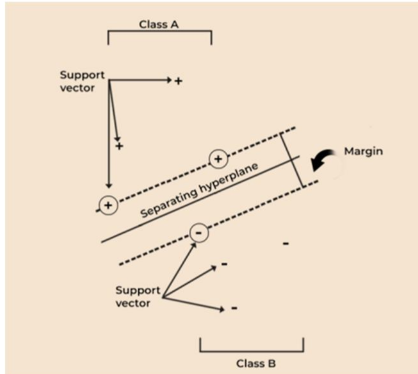

Fig. 8 Establishing the “margin” across subclasses, which is the criterion that SVMs are trying to improve

Attribute values are a subclass of preparatory stages that define where the dividing hyperplane should be positioned. Multiclass tasks are typically reduced to a string of binary conditions, and the basic SVM approach is created for binary classification. In this study endeavour, SVM is utilised to identify the EEG signals in mental stress or relaxed condition according to the flowchart provided in Fig. 9. The frequency bands comprise features of the classifier.

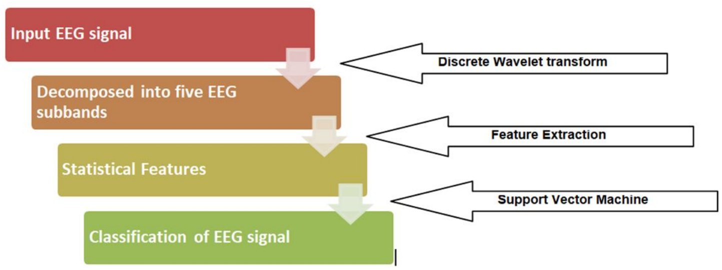

Fig. 9 Flowchart for SVM-based mental stress detection

2) RNN Algorithm

The RNN is really a supervised neural network arrangement that increases the show's performance on present and time-ahead data by applying knowledge from the previous. The presence of a hidden layer and loop characterises RNNs. The network's cyclical structure allows it to retain past data in a hidden layer and act on sequences. Because of these qualities, recurrent neural networks are exceptionally suitable to addressing many difficulties requiring sequential data of varying times, such as:

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

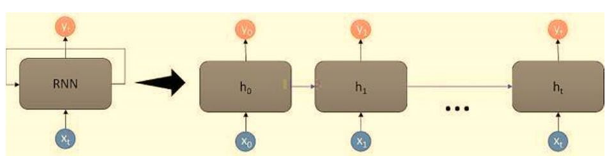

Fig. 10 An RNN cell is unrolled one at a time.

Fig. 10 depicts how a data series moves across the system. The hidden layer of the cellular unit functions on the components to generate the result, and the hidden layer is passed to another sampling interval. There are 2 kinds of network weights: one for obscured vector field and the other for the output outcomes. During activation, this network may learn the weight for both the input and the hidden layer. The output is dependent on the current intake and the hidden layer, reliant on prior input when enabled. The training technique is a conventional approach for training RNNs, and it may result in either a vanishing or an increasing gradient problem. The networking values could become very low or very high owing to these issues, reducing the effectiveness of constructing carriage returns. In this work, RNN is employed to detect stress similarly to SVM.

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3) LSTM Networks

Lengthy correlations among clock cycles of data sets may be detected using an LSTM model. A pattern-based input layer and an LSTM layer are the two primary components of an LSTM network. A sequential input layer transmits packets into the system in the form of a sequence or a time series. The long-term relationships among sequence data time steps are taught using an LSTM layer. Fig. 11 demonstrates the creation of a simple LSTM network for assessment. A sequence input phase is described by either an LSTM intermediate node. The network closes with a convolution layer, a soft-max layer, and a segmentation output vector to predict 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 develop 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 whole linked layer the same size as the class labels. Fig. 12 demonstrates the transport for time-series data X having C features (streams) of dimensions S across 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 ht and ct, respectively.

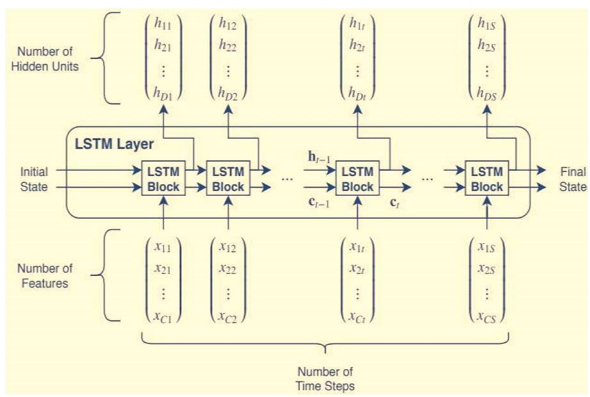

Fig. 12 LSTM Layer Architecture

The initial LSTM block computes the first result and the modified related output using the beginning state of the network and sequence's 1st phase. Using the current network state (ct−1, ht−1) then, the next periodic stride in the sequence, the module computes the result and the updated corresponding output ct at sample time t.

The concealed information (typically known as the output state), as well as the layer of the network, make up the layer's state. The output 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 saved in the cell state. The layer includes or subtracts data from the cell state at every sample interval. Furthermore, the layer includes or subtracts data from the cell state. The layer employs gates to regulate these changes. This image illustrates the flow of information at intervals t. The design in Fig. 13 depicts how the gating remembers, modifies, and emits the hidden and cellular states.

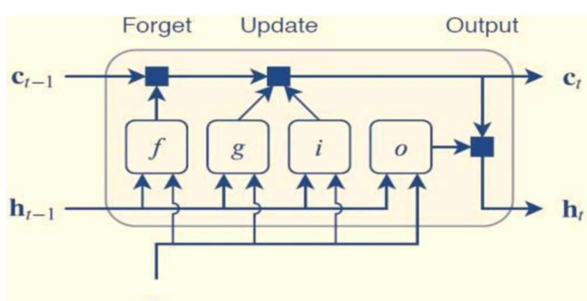

Fig. 13 Gates of LSTM Layer

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IV. PROPOSED RNN-LSTM ALGORITHM

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

The creation of a simple LSTM network for regression is depicted in Fig. 14. Sequential layers of inputs are sent to LSTM, which is further completely linked, and the output response is regressive.

To construct an LSTM model for sequential forecasting, a multi-arrangement with a pattern artificial neuron, an LSTM layer, completely connected layers, and a regress output unit is presented. A range of characteristics (EEG Frequency Bands) are placed within the data input to a length of the consecutive input nodes. A totally connected level the same size as the number of answers is thus produced. The suggested parallel fusion RNN-LSTM approach is represented in Fig. 15 as a flowchart.

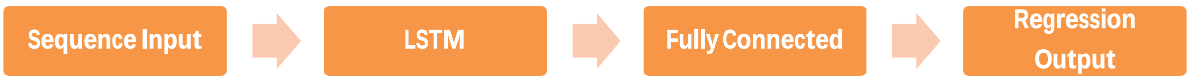

Fig. 14 a) RNN-LSTM Output

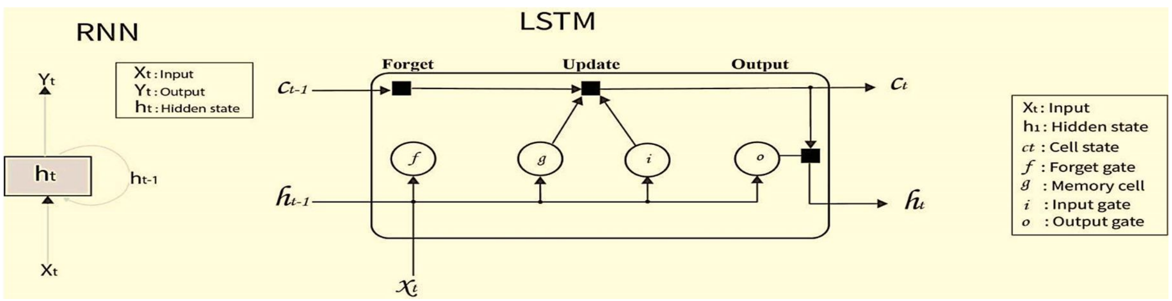

Fig. 14 b) RNN-LSTM Network layer

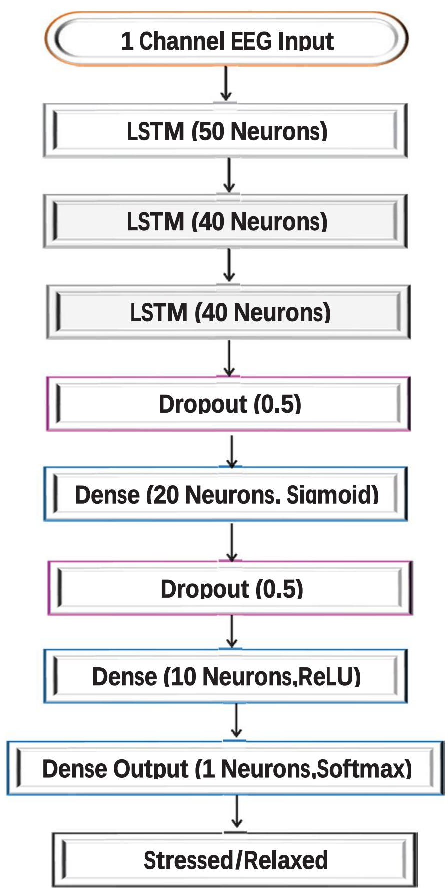

Fig. 15 Flowchart for LSTM with dropout layer

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LSTMs may selectively remember similarities for only a considerable duration, which is crucial for extracting information from physiological data. RNN, on the other hand, can swiftly determine the recurrence of patterns in a signal. To reduce over-training of sequence data from LSTM, the suggested strategy follows each fully - linked with a 0.5 single hidden layer that discards 50% of random features.

This data and information employ RNN, and then after dropping, the final FC layer is connected to the categorization hidden layers through to the softmax for LSTM condition classification. This approach is innovative and is one of the contributions of this study endeavour. A 50% decrease in random features minimises the data quantity to be handled, and conjunction for two classifiers boosts the accuracy of the outputs. It can be observed from Fig. 16 that following the feature extraction stage, RNN continues to sample the data; however, LSTM begins the classification process parallelly.

B. 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 indicated in Fig. 17. Data from 10 EEG signal sources are utilised to train the algorithms. Before training, data pretreatment, decomposition and feature extraction are done using wavelet transformation. The data from single-channel and its breakdown to distinct EEG frequency bands are given in Fig. 18.

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

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

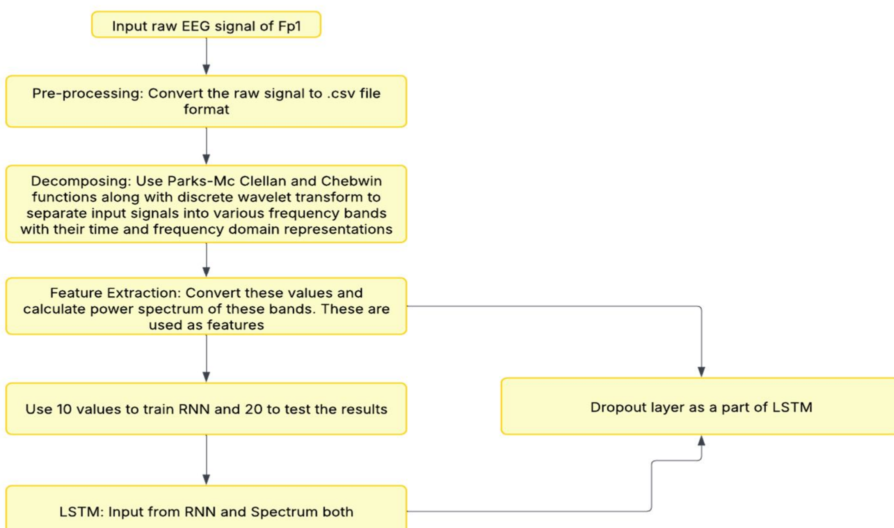

Fig. 16 The flowchart of the proposed RNN-LSTM combined for mental stress detection

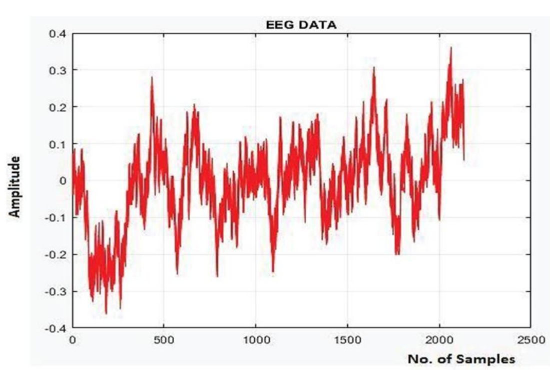

Fig. 17 EEG Signal from a stressed mind

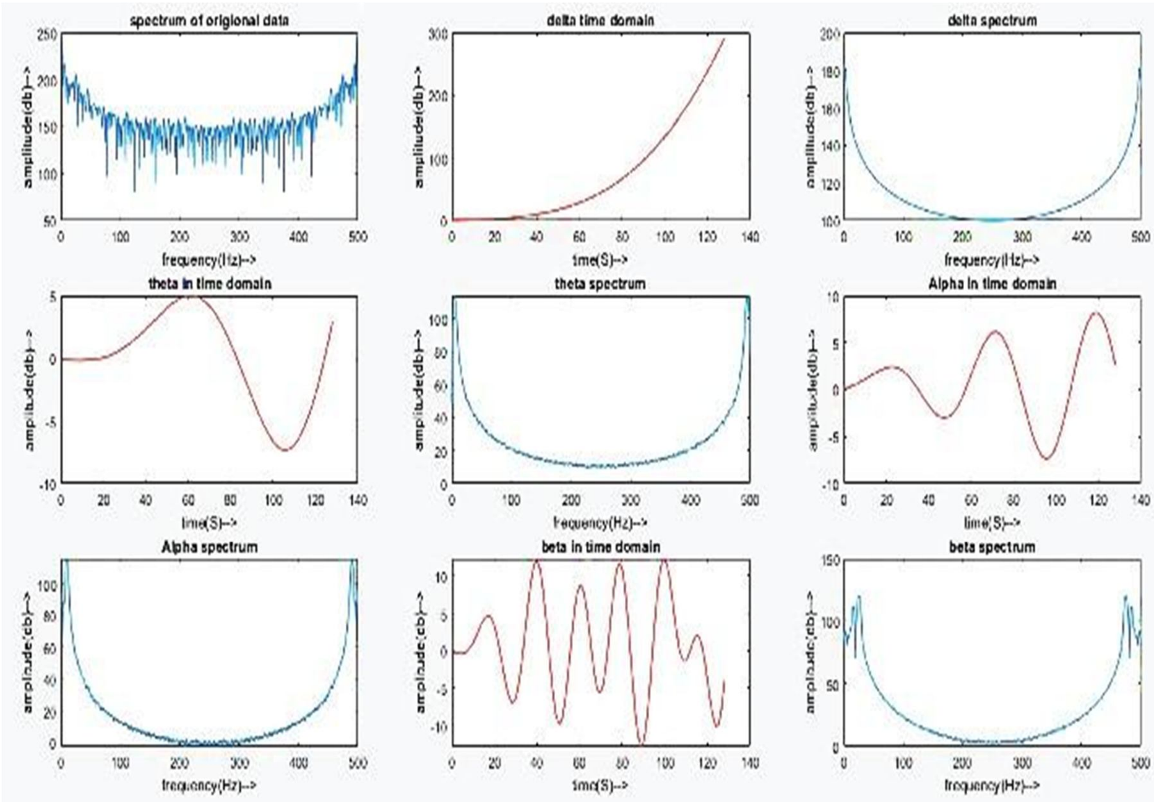

Fig. 18 Decomposition of EEG signals in different frequency bands

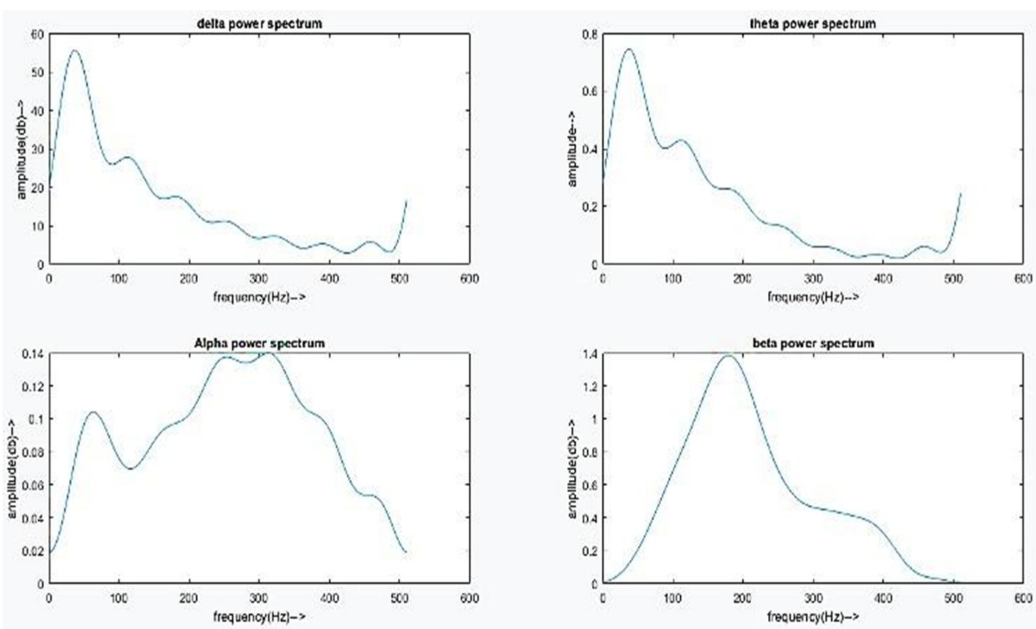

Fig. 19 Power Spectrum of different EEG frequency bands used as features

C. Testing of the dataset created

The writers partnered 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 supplied to him. The physician evaluated the EEG data received from the subject as agitated or calm, as stated in Table I.

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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
21	Stressed
22	Stressed
23	Stressed
24	Stressed
25	Relaxed
26	Stressed
27	Relaxed
28	Relaxed
29	Stressed
30	Relaxed

MATLAB-based methods were utilised to execute the trials. The knowledge on identifying the mental state from EEG and psychological and physiological data was taught to the algorithms utilising 10 markers from the available data. Around 33% of the data was utilised for training, while the remaining 67% was used to assess the effectiveness of the algorithms.

V. RESULTS AND DISCUSSIONS

A. 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.

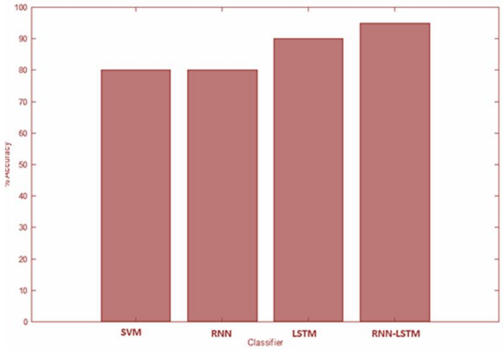

Fig. 20 Percentage Accuracy of classifiers for created dataset

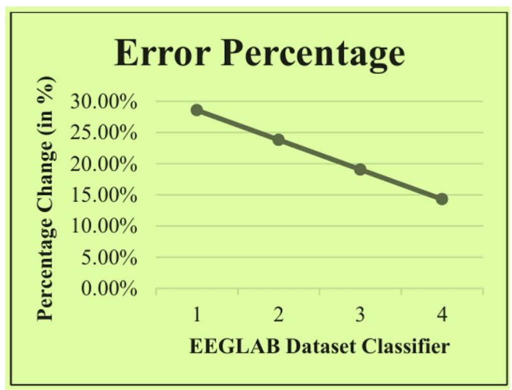

Fig. 21 Change in percentage error of SVM, RNN, LSTM and proposed RNN-LSTM of EEGLAB Dataset Classifier

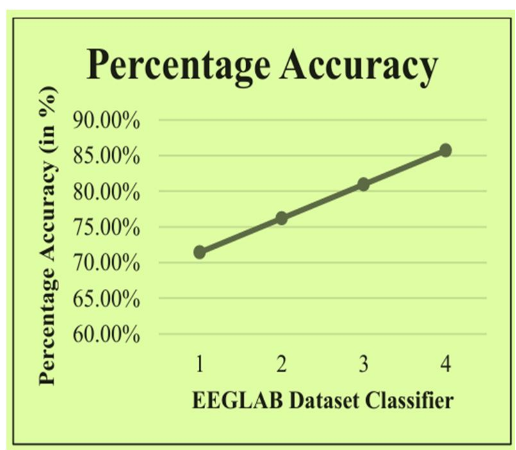

Fig. 22 Percentage accuracy of SVM, RNN, LSTM and proposed RNN-LSTM of EEGLAB Dataset Classifier

B. Testing the algorithms on DEAP Dataset

The development of the algorithm is evaluated 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 evaluated on 21 participants from the dataset, which categorise emotions into joyful and furious categories. For this study, the joyful state of mind is turned to a relaxed condition and the furious state is converted into a stressed one. In the dataset, there were 12 furious individuals and 9 cheerful people. The same EEGLAB dataset was utilised to train the algorithms.

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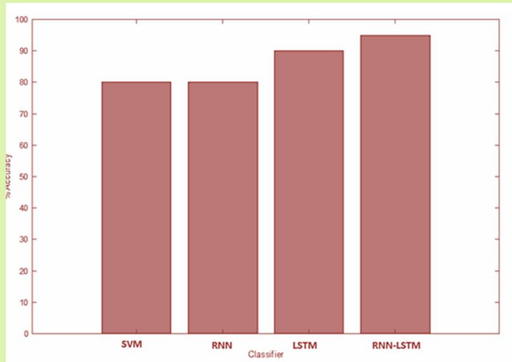

Fig. 23 Percentage Accuracy of classifiers for the DEAP dataset

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.

VI. CONCLUSION AND FUTURE DIRECTIONS

EEG data from a person's thoughts may be employed to differentiate many sorts of emotions. The machine learning algorithms were trained on a dataset of 10 EEG signals from the EEGLAB toolkit. Using a Neurosky Mindwave EEG headset, an EEG dataset of 20 patients from a well- known psychologist was gathered. To separate the signals into various frequency bands. To characterise the state of mind, an RNN-LSTM-based classifier was proposed and compared against current classifiers, including SVM, RNN, and LSTM. It was demonstrated that the proposed technique had an accuracy of 5% to 15% higher than older methods. Additionally, the DEAP dataset was employed to assess classifier accuracy for additional validation of findings, indicating that the new strategy performs better than prior strategies. The goal of this research's future work is to analyse a proposed algorithm for stress detection utilising speech signals. To design a unique algorithm for stress identification employing EEG and above signals and assess a suggested way for identifying stress using audio-visual inputs. The generated method is suggested for further assessment and application in a real scientific setting like research labs and medical institutions.

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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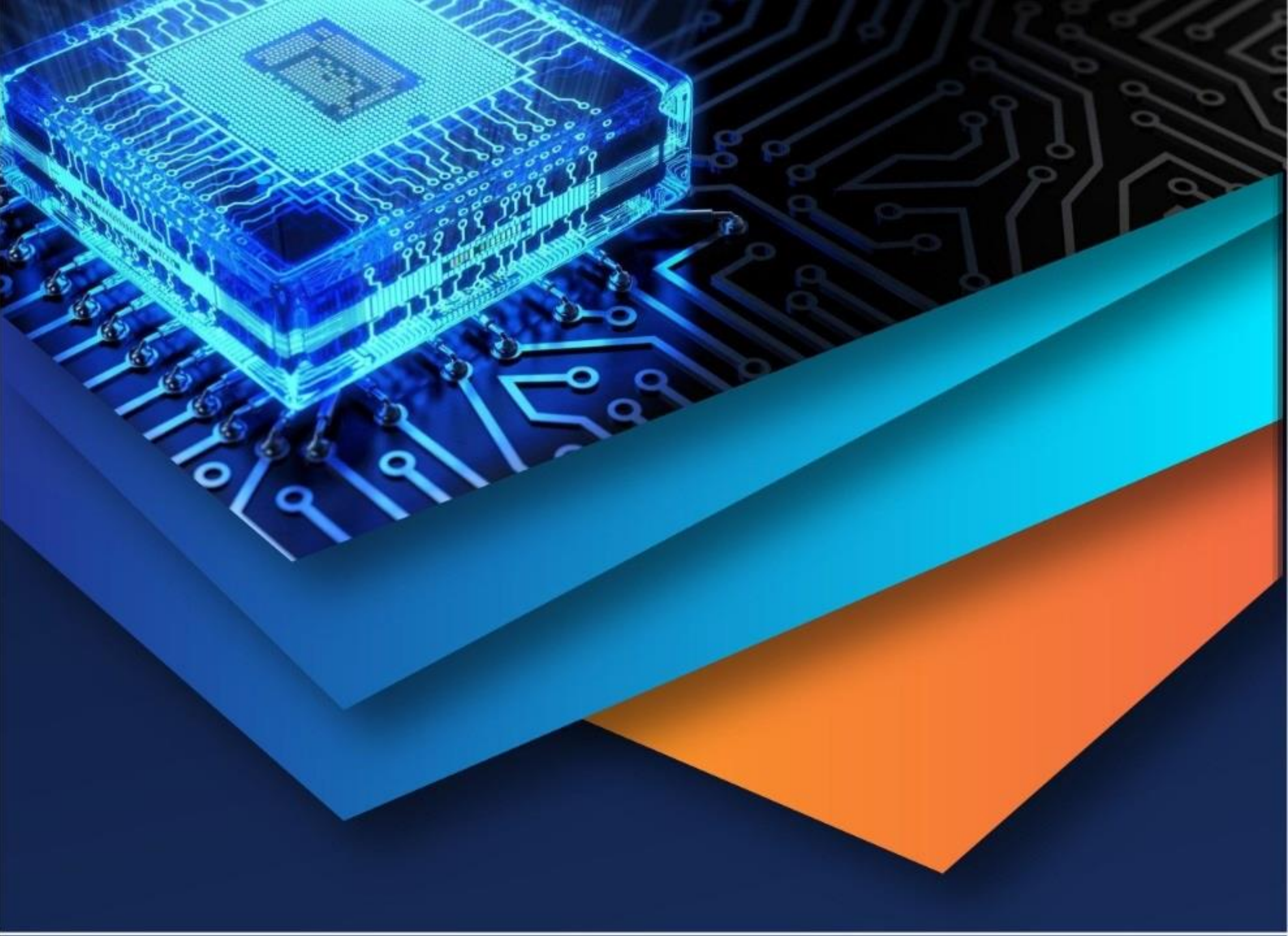

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