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Stress-Nets- A Novel LSTM Ensembled Single Feed Forward Layers for Stress Classification with EEG Signals

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Abstract: - Mental instability and emotional imbalance of the individual can be reflected in the form of stress which results in an inappropriate work ethics. There are various methods for the Stress creation. Moreover , several bio-signal sources such as Electroencephalograph(EEG), Electrocardiography(ECG) and Electromyography(EMG) are considered to be the important catalyst for developing the stress detection systems(SDS). Recently, machine and deep learning algorithms has gained more popularity in designing the SDS using the bio-signals. Further, EEG based SDS with ML and DL algorithms plays an important role for its high classification accuracy and performance. However, these EEG based SDS systems needs the better lime light of improvisation in terms of performance and computational overhead to deal with multiple datasets. In this context, this manuscript proposes new Long Short term Memory recurrent units(LSTM) for extracting temporal features while enhanced extreme learning machines are employed for better classification with less computational complexity. The different data sources are used to collect the EEG signals in which the collected signals are preprocessed for evaluating the proposed model. Additionally, the experiments are performed by DEAP and Kaggle datasets as well as performance parameters and compared by conventional Fused Support vector machines (F-SVM),BI-Long Short Term Memory(BILSTM), Random Forest(RF) and Deep Convolutional Neural network(DCNN). Results shows which proposed EEG based SDS has better performance than other conventional ones of high accuracy in stress detection and for diagnosing classify the stress-levels .

Keywords: EEG, ECG, EMG, Stress Detection Systems, Gated recurrent units, extreme learning machines, DEAP, Kaggle Stress datasets.

SECTION-I

I. INTRODUCTION

Mental Stress is measured most significant social issue in 21st century. It concerns individual's routine work, economy, as well as health. The stressful situation also evokes the stress hormones which are responsible for producing the unstable bio -electrical signals , results in heart pound, muscle tone and so on[1]. Stress affects the individuals across the all professions, that causes severe issue in life-threatening conditions. Additionally globalization , working diversity , hectic workloads are also increasing day by day , that remains serious threat to the humans [2] . Hence the reliable and high accurate measurements are mandatorily required for the early detection of stress.

Assume human cerebrum as initial source of stress [3,4]. To investigate degree of stress on dissimilar individuals, ample of stress detection and monitoring systems has been designed[5,6].

From the above methods, it is evident that body related signals such as electrocardiography(ECG), Electroencephalogram(EEG), electromyography(EMG) plays significant part in the development of SDS. Furthermore, EEG favors more attention than any other bio signals related SDS due to its dynamic behavior in accordance to the human activities. EEG are the continuous signals which is employed to evaluate electrical activity of brain. This signal is predetermined range of frequencies as well as amplitudes over time interval. EEG patterns includes alpha,theta, delta, beta and gamma waves. The early studies shows that the human thought processing and activities has its impact on the behavior of EEG waveforms. To classify the stress from the normal human feelings, EEG's dynamic behavior patterns plays a pivotal role and contributes the significant impact in designing the stress detection systems(SDS)[7,8]. Figure 1 shows the different EEG rhythms waveforms.

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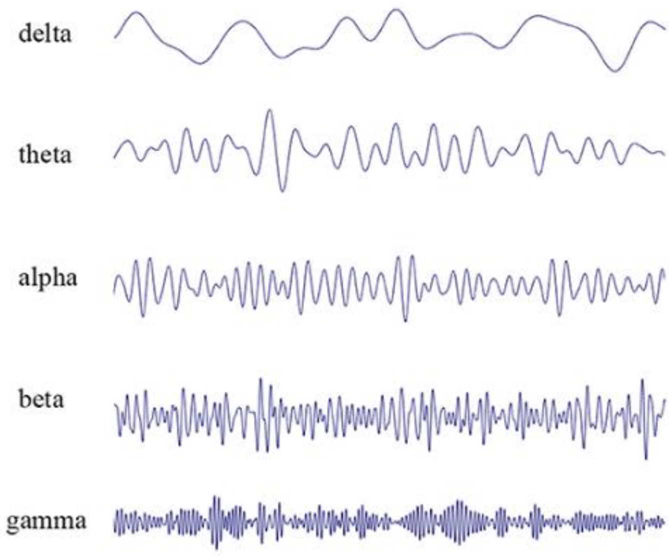


Figure 1: EEG with different frequency rhythms

EEG based SDS has some advantages such as low-cost, high resolutions as well as simplicity to use. Therefore it s mainly used method to examine mental stability of the human including the stress.[9-11]. Conventional methods such as used for EEG based stress detection[12-14] . But these methods suffers from the limitations such as low resolutions, less accuracy and imbalance extraction of features[15].

In recent time, rise of ML and DL algorithms has thrown the bright light in designing the EEG based SDS. Many algorithms such as SVM [16], DNN[17], LSTM[18] are used for developing an efficient stress detection system. However , these methods needs the improvisation in terms of high stress detection and less computational complexity. Furthermore, these learning models fails when handling the multiple datasets. To overcome this above issue, this manuscript proposes STRESS-NETS- a new ensemble of LSTM with Enhanced Extreme Learning Machines(EELM) to get the better accuracy for the multiple datasets. To finest of our knowledge, the proposed network is primary of its kind to handle the multiple stress to attain improved classification accuracy.

CONTRIBUTION OF PAPER :

1. The manuscript proposes new hybrid LSTM network in that traditional dense layers are replaced with enhanced extreme learning machines to handle multiple EEG datasets.
2. Extraction of the temporal features from EEG signals has been proposed for the better training and validation.
3. Performance of proposed network has estimated by multiple EEG stress datasets and compared with other conventional learning based EEG-SDS.

Remainder of manuscript is structured as below : **Section-II** describe literature review proposed during over one authors. Working method of designed framework are explained in **Section-III**. Experimentations, outcomes, findings as well as study are describedin **Section-IV. Section-V** manuscript is concluded through future improvements

SECTION-II

II. LITERATURE REVIEW:

S. Chambon introduced DL based framework for stress detection and this framework collects the data during night time and records the data as EEG signals. To represent the features of raw input signals this framework adopts backpropagation based learning approach. This framework helps to predict locations and event types. Experimental findings on spindles and K-complexes detection demonstrates which this framework outperformed other approaches. Positive side of this framework is it can easily detect multiple type of events. Negative side of this framework is, it is hard to discover people who are really stressed however fewer associated to social media [23].

I. Madhavi concentrated on work related stress recognition in cyber physical scenario with help of audio streams. This framework adopts CNN and GSOM framework to prove excellence in noise elimination as well as feature extraction. Fourier transform as well as speech augmentation techniques are also involved to extract low level features and to address imbalance in the data respectively. CNN quickly study high level features and significantly reduces the dimensionality. These are fed as the input to GSOM algorithm, in order to create topology protecting feature maps. Main advantage of this framework is it is highly robust for cyber physical scenarios and disadvantage is this framework is little bit expensive to implement in real time [24].

Hyewon Han make employ of speech signals for stress recognition with help of DL algorithms. Initially this framework extracts the mel-filterbank coefficients by preprocessed speech data, the LSTM and feed forward network are utilized to predict the stress status based on binary decision criterion. For the evaluation process data were gathered in well-defined environment. The speech signals were only taken for decision making process whose salivary cortisol level fluctuates over 10%. This framework achieves accuracy of 66.4% in stress detection from 25 objects. But computational complexity was not reduced, when the data set size increased [25].

Russell Li presented stress detection framework which has 2 NN (Neural Network) namely CNN and MLP. It computes physiological signals from chest and wrist worn, to do 2 functions named binary stress recognition and 3 class emotion classification. For above mentioned 2 functions, this framework provides better results when contrasted with other frameworks. Finally this framework states that this framework is highly suitable for emotional classification and stress detection because it comprises of robust and noninvasive techniques [26].

Z. Zainudinanalysed mental health in real time envieonment by collecting dataset from IoT using sensors. To design a stress detection pattern, the data are colleceted with the help of sensors called GSR (“Galvanic Skin Response Sensor”) and ECG (“Electrocardiogram”). This framework utilized techniques called SVM, DT, MLP, KNN and DL algorithm to categorize the collected dataset. Final results are evaluated in accuracy, recall, precision in addition to F1 score. Experimental finding suggest DT method is suitable for stress detection because it achieved 96% of precision, 95% accuracy and 96% of F1score and 96% of recall among all the available ML techniques for stress detection [27].

A. Liapis utilized dataset called WESAD (wearable stress and affect detection) for stress detection. The Skin temperature and Electro dermal activity signals from the WESAD is utilized for the train classifiers models namely L-SVM, Q-SCM, Q-SVM. This framework solves the binary classification problem for the stress detection and provides impressive results in user experience evaluation. More specifically this model achieved high accuracy when user-annoted dataset was utilized for the experimentation [28].

ReshmaRadheshamjeeBaheti proposed a stress detection technique by using social media information. Especially this framework utilized twitter dataset for the analysis of emotions. It has the scale ranging from -5 to +5 for the classification of positive and negative emotions. These emotions are categorized as stress and relax. The SVM and NB methodologies are utilized for the stress detection and classification. To enhance outcome accuracy executed WSD (“Word Sense Disambiguation”) through n-gram as well as Skip-gram method. It results in 65% precision, 67% recall. But negative side of this framework is it only utilized the text data and excludes the symbols and emojis for stress detection and classification [29].

AvirathSundaresan developed a stress detection framework using EEG signals in real time This framework is a DL based EEG anxiety classifier to analyze adolescents with autism as well as neuro typical adolescents. Also, it compared different ML classifiers and deep learning methods. Among all classifiers, the 2 layer LSTM finds betters result in stress detection and shows accuracy of 93.27%. This framework is capable of monitoring stress periods by adapting breathing patterns. But major disadvantage of framework is, it struggles when handling huge datasets and leads to computational complexity [30].

B. Padmaja introduced framework to detect cognitive stress levels by utilizing knowledge from physical activity tracker device designed via FITBIT. This framework adopts sensor technology with the ML algorithm for the stress detection. For the evaluation of this framework done in real time environment and logistic regression technique is utilized. This is a noninvasive method and helpful for all kind of users. Based on the sleeping measurement and BMI of person, the stress level is classified. Because sleeping and BMI is directly connected with stress levels. But major downside of this approach is, it increases time complexity when the dataset size is increased [31].

AnuPriya developed a framework to predict anxiety, depression as well as stress levels through help of ML algorithms. For the evaluation of this framework, data were gathered from different employed as well as unemployed individuals across various communities and cultures via “Depression, Anxiety and Stress Scale questionnaire” (DASS 21). Totally 5 classifiers are incorporated for evaluation namely DT, RFT, NB, SVM and KNN. Among all the evaluated classifiers NB gives best accuracy and RF is suggested as best method due to its imbalanced data classes handling capacity. But major disadvantage of this framework is it excludes the data in the form of emoji’s and symbols. Also, it implementation of this framework in real time is more expensive [32]

SECTION -III

III. PROPOSED FRAMEWORK

Designed framework contain Data collection (ii) pre-processing as well as filtering (iii) Temporal feature extraction by LSTM (iv) Classification (Stress) .

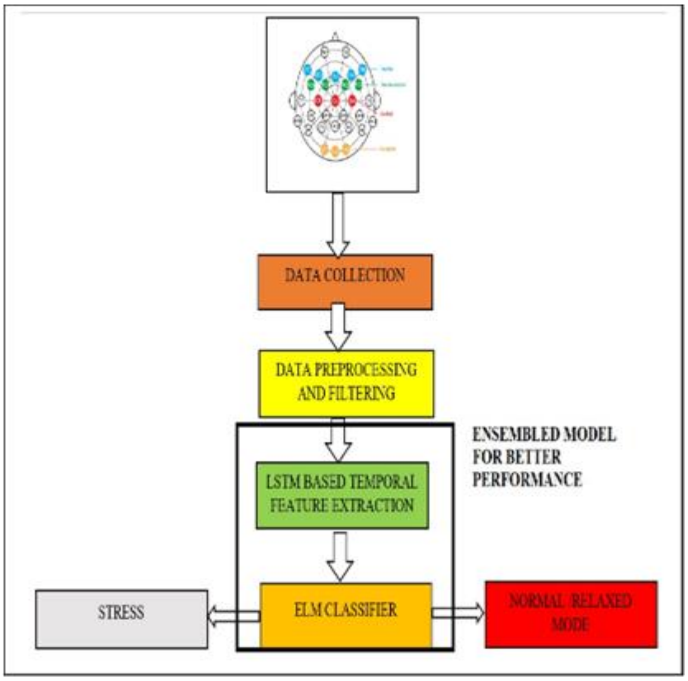


Figure 2: Block diagram for the Proposed framework

3.1 DATA COLLECTION UNIT :

Different datasets are employed in this work to verify classification superiority of proposed model. Detailed description of detests are depicted as follows

3.1.1 DATASET-1 : The dataset-1consist of EEG signals from physio bank[33]. It contain EEG records of 36 subjects by 10-20 international scheme. Information was recorded as carried out cognitive mental workload; in this case, it multifaceted serial subtraction. Each recording consist of artifact free EEG of 182sec for baseline state as well as 62sec for task performing state.

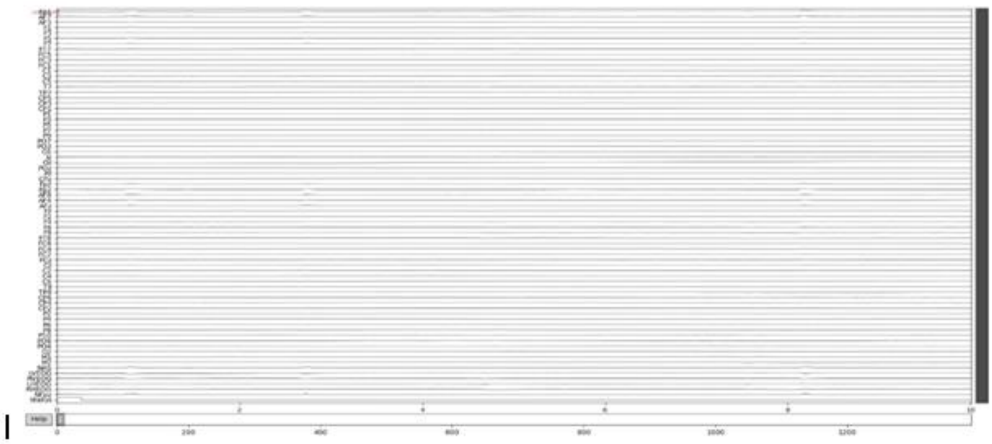
3.1.2 DATASET-2 : This dataset-2 is constructed based on the [34]. This datasets contain EEG records of 26 subjects by 10-20 international scheme. Around 26 human subjects through normal vision of average age of 25 years volunteered for study.

3.1.3 DATASET-3 : The dataset-3 used in this work is DEAP datasets[35]. The datasets consist of 48 recorded channels at 512Hz. Information was recorded in two segregate position. Participants 1-22 were recorded in Twente and participant 23-32 in Geneva. Because of dissimilar amendment of hardware, there is small variation in format. Main objective to categorize EEG data as normal or stress. Table I presents the total number of EEG data employed for an efficient binary classification.

Table I: Consolidated Number of Datasets Used for Evaluating the Proposed Model

Sl no	Datasets Description	Total No. of normal data	Total no. of Stress data	Total Data used for evaluation
1	Dataset-1	91000	31000	1,22,000
2	Dataset-2	86700	54345	1,41,045
3	Dataset-3	15679	23478	39,157

(a)



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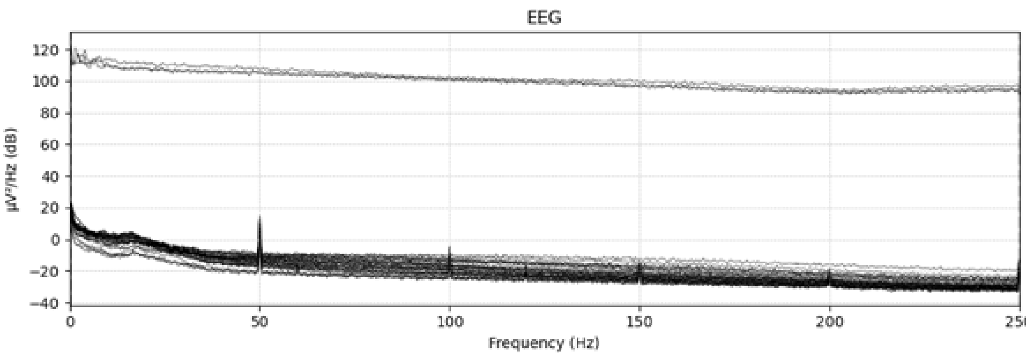

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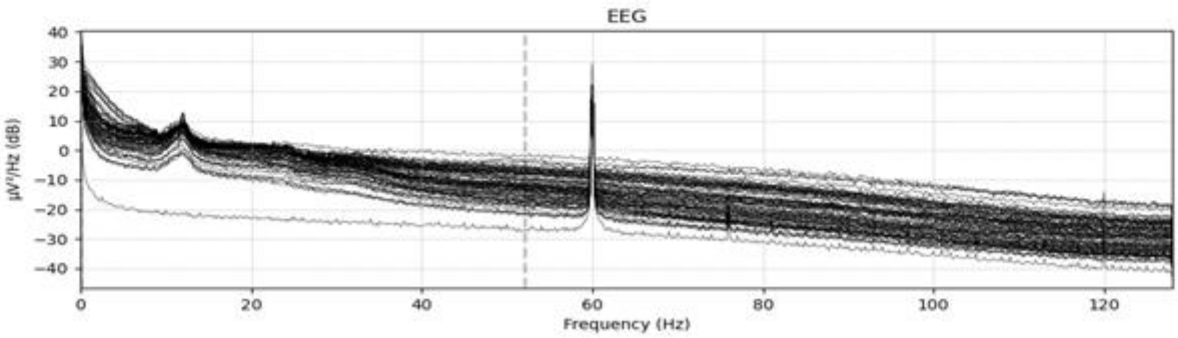


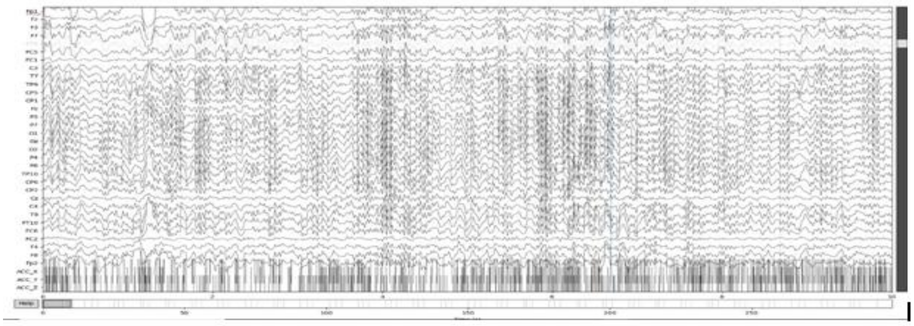
(d)

Figure 3: Sample RAW EEG Waveform from a) Dataset-I c) Power spectral density of Sample signal (Dataset-2)

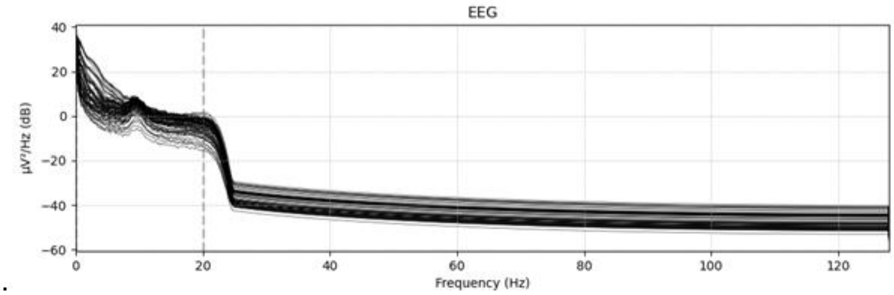
3.2 EEG PREPROCESSING AND FILTERING :

In biomedical signal, fortitude of noise in obtained signal is essential to shift to feature extraction stage during clean signal as well as attain better classification outcomes. For the aim of denoising and artifacts , this paper employs the MNE-python based libraries[36] to filter pertinent sub-bands of EEG signals , eradicating baseline we have used python and MNELAB script helping to slash pertinent sub-band of EEG signals, eradicating baseline as well as eradicating Ocular as well as Muscular artifacts. Figure 4 shows the MNELAB tool used for pre-processing and sampled filtered signal is shown in Figure 5

Figure 4: Python based MNE_LAB used for the EEG preprocessing and Filtering



(a)



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(b)

Figure 5: EEG preprocessing and Filtering Signals – a. Preprocessed and Filter Signal; b. PSD of the Preporocessed

3.3 PROPOSED HYBRID MODEL :

Figure shows designed hybrid model employed for feature extraction and classification layer of stress data . This section details about the LSTM network for the temporal feature extraction and enhanced EL machine employed for efficient classification of EEG data.

3.3.1 LSTM NETWORK BASED FEATURE EXTRACTION :

In RNN, unobserved layer of every NN is connected to hidden layers of other nodes of another novel network. As per recurrent NN, nodes of similar hidden layers are associated together. RNN is developed for time series, big-data because of its commemoration motion as well as encode historical information in little ms.Direct form of graphs can produced through nodes through their So, RNN employs chronological data to forecast upcoming values. In realistic applications, when intermediate time among previous information is huge, it cannot memorize previous information in momentous method, therefore there is still disappearing gradient issue, so that outcomes attained are not acceptable in real-time application. To alleviate this problem, RNN performance has improved by introduction of LSTM network.

3..3 .2LSTM :

LSTM is a trendy learning method which used for numerous applications because of its flexibility in memory as well as more suitable for enormous database. LSTM network has depicted in Figure 4.

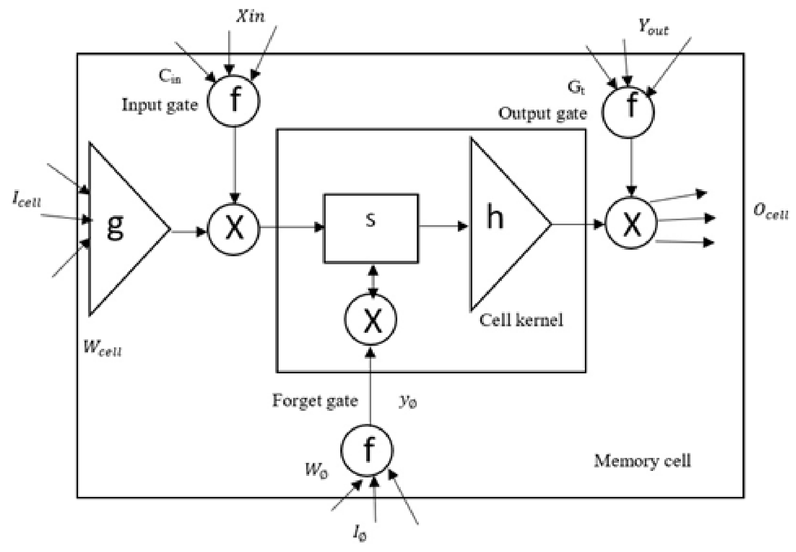


Figure 4: LSTM Structure

LSTM contain input gate (I.G), forget gate (F.G), cell input (C.I) as well as ouptu gate (O.G). Usually, LSTM is memory-based NN that to remember values behind each iteration. Let x_t, unobserved layer output is 'ht' as well as its former output is 'ht−1', cell input state is 'Ct', cell output state is 'G_t' as well as its former state is 'G_{t-1}', three gates' states are j_t, T_f as well as T_0. Structure of LSTM resembles which "G_t and ht" are conversed to after that NN in RNN. LSTM combines output of preceding unit through present input state in that O.G and F.G are employed to update memory. For computing G_t and h_t, employ below equations.

I.G:$j_t = \theta\left(G_l^i \cdot O_t + G_h^i \cdot e_{t-1} + s_i\right)$ (1)

$F \cdot G{:}T_f = \theta\left(G_t^f \cdot O_t + G_n^f \cdot e_{t-1} + s_f\right)$ (2)

$O.G{:}T_o = \theta(G_l^0 \cdot O_t + G_h^o \cdot e_{t-1} + s_o)$ (3)

C.I:$\widetilde{T_C} = \tanh\,(G_l^C \cdot O_t + G_h^C \cdot e_{t-1} + s_C)$ (4)

$G_i^0, G_i^f, G_i^f, G_i^c$ represents the weight matrices among I.G, output layers, $G_h^f, G_h^f, G_h^\circ, G_h^c$ denotes weight situation created among hidden as well as input layers. The " s_i, s_f, s_0, s_c are the bias vectors and tanh is considered to be hyperbolic function". G_t is estimated below

$T_c = k_t * \widetilde{T_C} + T_f * T_{t-1}$(5)

$e_t = T_0 * \tanh\,(T_C)$ (6)

Last output score is attained by above equation. The LSTM with dropout layers are used to learn the temporal features of pre-processed EEG signals and these features are employed to train classification layers of method. Proposed model replaces traditional dense layers with enhanced extreme learning layers to increase the high accuracy with less computational complexity.

3.4 EXTREME LEARNING LAYERS :

EL machines designed in G.B.Huang[37], in that network employs one hidden layer, enhanced speed as well as accuracy and preparing velocity. universal function approximation [38].

In this type of scheme, L' neurons in hidden layer are needed to work through activation function which is hugely variable , though which of output layer is direct. In ELM,hidden layers does not required to tunes mandatorily. In ELM, hidden layer forcibly require not tuned.

Loads of hidden layer are randomly selected. It isn't condition which hidden nodes are immaterial, but require not tuned as well as hidden neurons metrics arbitrarily created in proceed.

For solitary-hidden layer ELM, scheme yield is provided in eqn (7)

$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta$ (7)

Where x input

β output weight vector and it provided below

$\beta = [\beta_1, \beta_2, \dots\dots\dots\dots \beta_L]^T$ (8)

H(x) output hidden layer that given following eqn

$h(x) = [h_1(x), h_2(x), \dots \dots \dots \dots h_L(x)$ (9)

To establish Output vector O that is named as target vector, hidden layers are indicated in eqn (9)

$$H = [h(x_1)h(x_2) \vdots h(x_N)](10)$$

Fundamental execution of ELM employs lesser non -linear least square techniques that denoted byeqn (10)

$\sigma' = H^{*}O = H^T(HH^T)^{-1}O$ (11)

H∗□ inverse of H called as Moore−Penrose generalized inverse given as follows

$\beta' = H^T\left(\frac{1}{c}HH^T\right)^{-1} O$ (12)

Therefore output function discover by eqn(12)

$f_L(x) = h(x)\beta = h(x)H^T\left(\frac{1}{c}HH^T\right)^{-1} O$ (13)

ELM uses kernel function to give better exactness for enhanced peformance. Benefits of ELM are lesser training error. Elaborated explanation of ELM 's equations in [37],[38]. Traditional ELM requires optimization technique to get the better performance in detecting the mental stress. Many algorithms namely GA, PSO, BAT are used for optimization but these algorithm provides the very little effect on performance when handling the multiple datasets due to its low convergence speed. Hence this work introduces the enhanced version of ELM whose hyperparameters are optimized whale algorithm.

3.5 WOA:

Mirjalili et al. created well-known optimizer named Whale Optimization Algorithm(WOA) by [41]. This population based optimizer is devised depend on behaviour as well as movement of humpback whales for food as well as provisions. Hunting mode of humpback whales popular for finest result in numerous optimization issues. This algorithm, study procedure depend on comparative location of whale is indicated through random search for food, that analytically construed through apprising mature solutions . To this behaviour, WOA is particularly eminent from further algorithms since it needs two metrics. These metrics allow simple conversion among exploitation as well as exploration processes.

Figure 5: Encircling Attack Prey Searching methodology for Humpback Whales

Hunting range: through cumulative number of recurrence from begin to end, humpback whales are hunting around as well as updating their location into good search agents.

If (p<0.5 and mod(U)<1)

After that location of candidate situation X(t+1) as following equations.

$F = \mathrm{mod}\{(B \cdot X) - X(t)\}$ (14)

$X(t+1) = [X(t) - \{U.F\}]$ *(15)*

p =0.1 (constant) X(t+1) is finest location in present condition . U , D are estimated through equations(9) and (10)

$U = \text{mod}\{2 * a * r - a\}$ (16)

$B = 2 * r$ (17)

a is linearly reduces from 2 to 0 , r is arbitrarily chosen vector

Prey Searching : X is reinstated by arbitrary variables X_{random} equation as follows

F = mod { (BX_{random}) -X(t)} (18)

X(t+1) + [X_{random} (t) – {U.F}] (19)

Encircling prey as well as spiral updation of prey completed through exploration stage of WOA . Updation of novel location through spiral procedure is provided equation (13)

$$X(t+1) = D^{l}.e^{bl}.\cos(2\pi l) + X^{*}(t) \quad (20)$$

D is distance among novel as well as updated position in new generation.

3.6 ENHANCED EXTREME LEARNING CLASSIFICATION LAYERS

Though ELM offers better performance, its characteristics of random allocation of bias weights degrades its classification accuracy. Hence the enhanced extreme learning machine is constructed with the ELM with WOA. For every iteration, input bias as well as weights are estimated by equations(14),(15) and (20) and are feed to ELM network which fitness function are computed . If fitness function is equivalent to threshold , after that iteration ends or iterated incessantly.

Steps	Algorithm-1, Enhanced Extreme Learning Classification
1	Input: Input Bias weights,
2	Output: Maximum Classification
3	Initialize the Input bias weights using Equations(14),(19) and (20)
4	While N = 1 : max iteration
5	Find the best position using Equation(20)
6	Calculate the fitness function using Equation(21)
7	If best position == fitness function
8	Stop the Iteration
9	Else
10	Update Input bias weights using Equations(14),(19) and (20)
11	Find the best position using Equation(20)
12	Calculate the fitness function using Equation(21)
13	Go to Step 5
14	End
15	End
16	End

The EELM is used to train the temporal features from LSTM which can be employed for better classification of stress as well as normal state of human. Optimized parameters used for EELM classification is presented in table II

Table II Optimized Parameters used for Proposed Model to classify the stress data

Sl.no	Parameters	Specification
01	LSTM layers	02
02	No of Hidden layers in EELM	200
03	No of epochs	100

04	Batch Size	40
05	Leaming Error Rate	0.001
06	Dropout	0.2

SECTION-IV

IV. RESULTS

Table III presents mathematical expression for accuracy, precision, recall, specificity as well as F1-score employed for evaluating proposed network .Additionally , we have estimated AUC , confusion matrix to confirm supremacy of proposed method. Higher scores of parameters denotes enhanced performances. To resolve network's overfitting issue and enhance generalization issue, untimely stopping technique is employed in manuscript. As discussed in Section 3.1, more than 100000 datasets were collected in that 70% is considered as training , 30% as testing.

Table III. Mathematical Expressions for the Performance metrics' Calculation

SL.NO	Performance Metrics	Mathematical Expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Recall	$\frac{TP}{TP+FN}\times 100$
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1 - Score	$2.\frac{Precision * Recall}{Precision + Recall}$

The experiment was conducted on six different datasets and results of experiments were estimated and calculated against F-SVM, CNN+LSTM,LSTM,BILSTM,LSTM+SVM HCF+SVM and 2DCNN+LSTM.. Entire model was developed by opensourceTensorFlow version 2.1.0 with keras as backend and executed on PC workstation by 16GB RAM and 3.5 GHZ OF .

LABEL	STRESS	NORMAL
STRESS	98.7%	1.0%
NORMAL	1.1%	98.8%

(a)

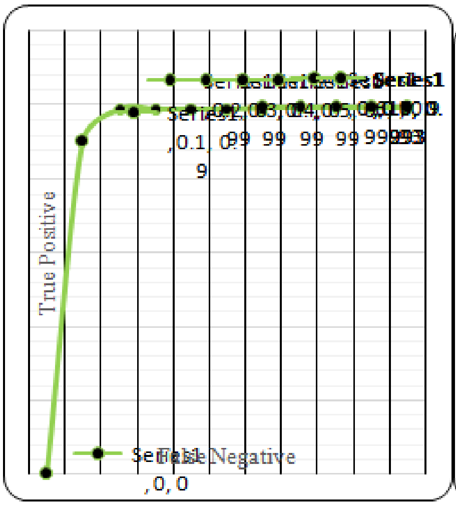
LABEL	STRESS	NORMAL
STRESS	98.9%	1%
NORMAL	1%	98.9%

(b)

LABEL	STRESS	NORMAL
STRESS	98.86%	1.2%
NORMAL	1.1%	98.89%

(c)

Figure 6: Confusion Matrix for Proposed method for using a) Dataset-1 , b) Dataset-2, c) Dataset- 3



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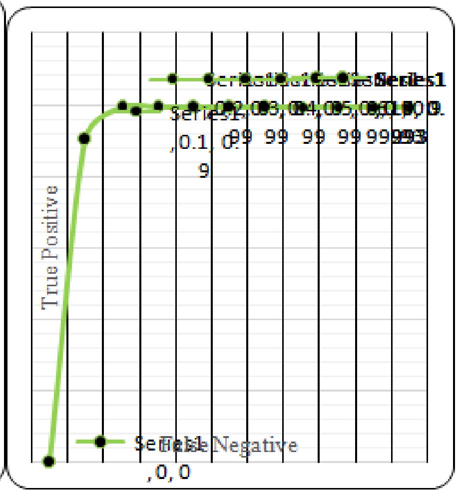

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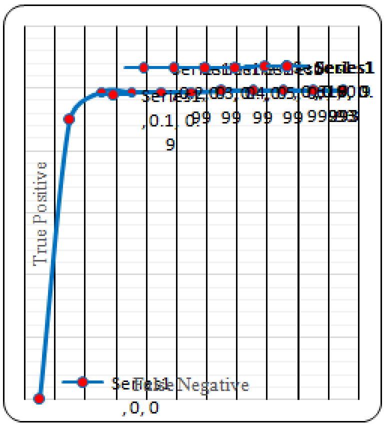
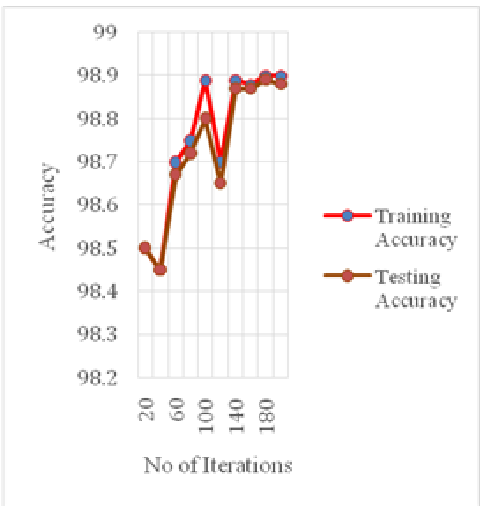
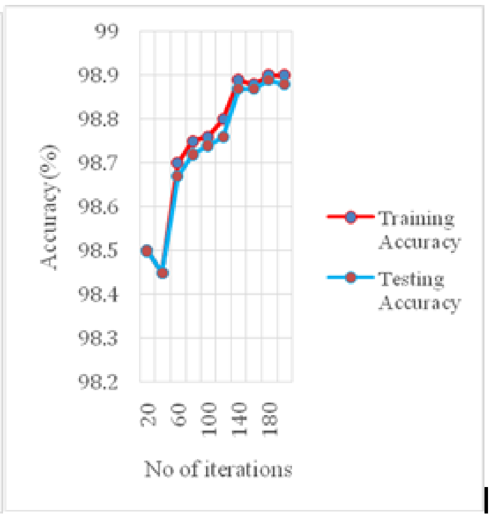


(c)

Figure 7 Roc Characteristics of Proposed Network a) Dataset -1 b) Dataset -2 c) Dataset-3



(a)



(b)

Figure 8: Validation Curves for Dataset-1 ; a) Normal Detection, b) Stress Detection

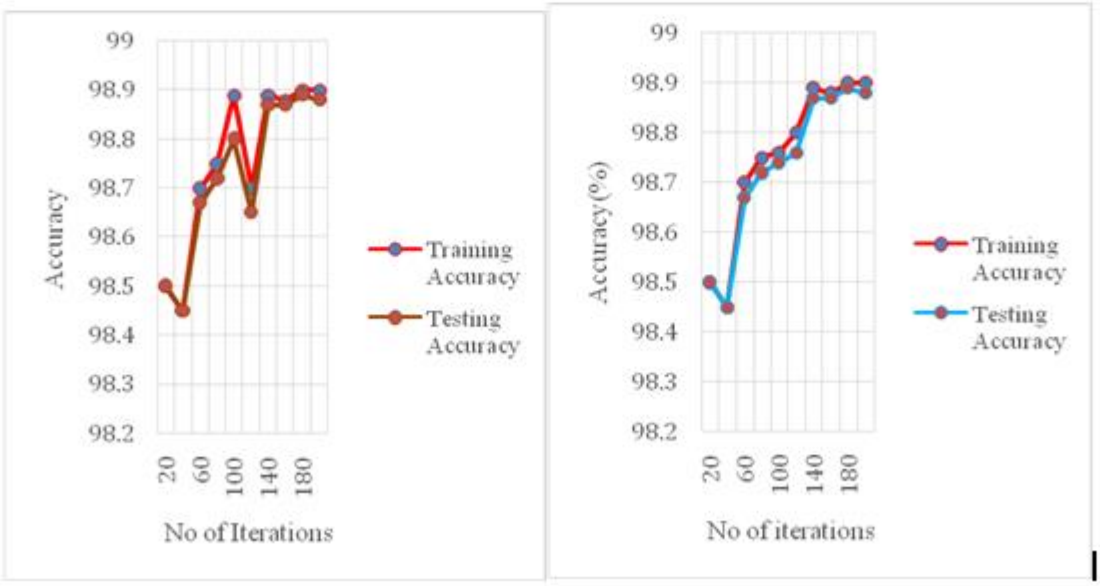


Figure 9: Validation Curves for Dataset-2; a) Normal Detection , b) Stress Detection

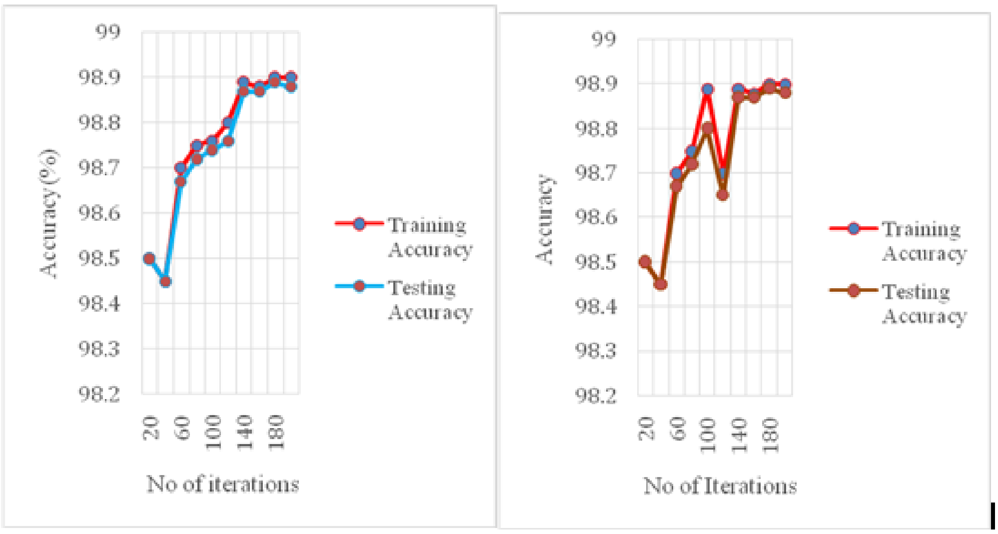


Figure 10: Validation Curves for Dataset-3; a) Normal Detection , b) Stress Detection

Confusion matrix , ROC curve of proposed modelin classification of stress using the three different data sources. Figures (9),(10),(11) shows the validation curve for proposed model with three datasets. It is found which proposed model has exhibited lesser error during training . Table IV presents performance parameters of proposed algorithm under three various datasets. From the table IV, it is found that the STRESS-NETS has exhibited the constant performance in classifying stress with three datasets.

Table IV: Performance metrics of the proposed model with the three datasets

Datasets	Performance Metrics				
	Accuracy	Precision	Recall	Specificity	F1-score
Dataset-1	0.9880	0.982	0.987	0.988	0.989
Datasets-2	0.9880	0.983	0.9865	0.989	0.988
Dataset-3	0.9879	0.9821	0.9869	0.990	0.989

Table V Comparison between the Performances of the Different Models using Dataset-1

Datasets	Performance Metrics				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
F-SVM	0.91	0.892	0.883	0.880	0.892
BI-LSTM	0.89	0.851	0.875	0.856	0.867
LSTM+CNN	0.92	0.901	0.923	0.93	0.90
LSTM+SVM	0.91	0.892	0.923	0.92	0.910
LSTM	0.80	0.790	0.81	0.80	0.805
2D- CNN+LSTM	0.902	0.902	0.90	0.91	0.92
HCF+SVM	0.89	0.87	0.894	0.82	0.82
Proposed Learning model	**0.9879**	**0.9821**	**0.9869**	**0.990**	**0.989**

Table VI: Comparison between the Performances of the Different Models using Dataset-2

Datasets	Performance Metrics				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
F-SVM	0.91	0.892	0.883	0.880	0.892
BI-LSTM	0.89	0.851	0.875	0.856	0.867
LSTM+CNN	0.92	0.901	0.923	0.93	0.90
LSTM+SVM	0.91	0.892	0.923	0.92	0.910
LSTM	0.80	0.790	0.81	0.80	0.805
2D- CNN+LSTM	0.902	0.902	0.90	0.91	0.92
HCF+SVM	0.89	0.87	0.894	0.82	0.82
Proposed Learning model	**0.9880**	**0.983**	**0.9865**	**0.989**	**0.988**

Table VI: Comparison between the Performances of the Different Models using Dataset-3

Datasets	Performance Metrics				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
F-SVM	0.91	0.892	0.883	0.880	0.892
BI-LSTM	0.89	0.851	0.875	0.856	0.867
LSTM+CNN	0.92	0.901	0.923	0.93	0.90

LSTM+SVM	0.91	0.892	0.923	0.92	0.910
LSTM	0.80	0.790	0.81	0.80	0.805
2D- CNN+LSTM	0.902	0.902	0.90	0.91	0.92
HCF+SVM	0.89	0.87	0.894	0.82	0.82
Proposed Learning model	**0.9879**	**0.9821**	**0.9869**	**0.990**	**0.989**

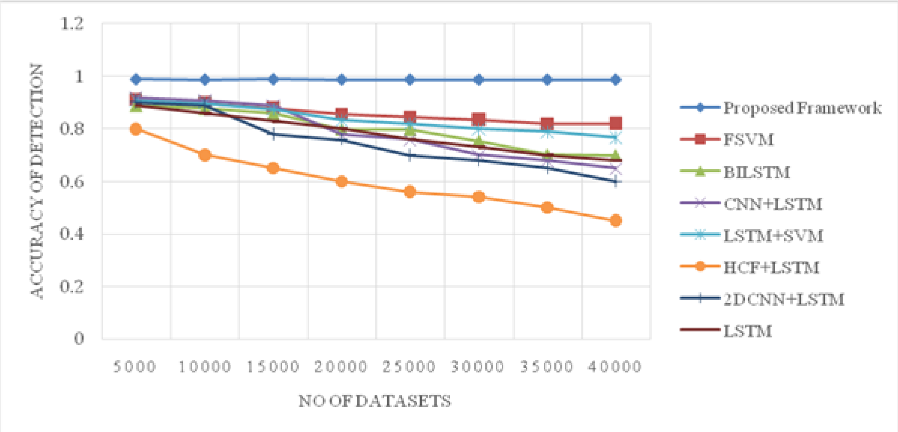


Figure 11 Behavior of the Different Framework for the Increased Datasets

Table V to VII describe comparative study between performances of proposed as well as conventional algorithms. From tables , STRESS-NETS has outperformed other existing learning using three different datasets. The integration of enhanced extreme learning machines with LSTM network has proved its excellence over the other existing algorithms. Figure 11 shows performance of different algorithms with improved number of combined datasets. Inclusion of EELM with LSTM in STRESS-NETS has shown the stable performance as the number of datasets increases. The other existing algorithms has shown a dip in their performance with the increased datasets.

SECTION -V

V. CONCLUSION:

Major objective of research is to identify as well as classify stress from EEG using novel ensembled DL algorithm. To classify stress from EEG stress data, LSTM is major layer and dense layer is replaced with enhanced extreme learning classification layers, which are employed to train network for improved classification. Three different EEG information sources were employed for the training and validating proposed method. Collected EEG signals are preprocessed ,filtered and given as input to proposed method. LSTM proposed model is used to extract temporal features and EELM is utilizedto classify the stress from the EEG signals. Outcomes demonstrate that proposed architecture has better than the other conventional architectures and attained maximum outcomes namely 99.89% accuracy,99.8% sensitivity and specificity, 99.86% precision as well as 99.89% F1-score. Additionally, simulation results shows which proposed algorithm has demonstrated the stable performance as number of datasets increases. In future, proposed method requires an improvisation in less- complexity to fit in to future generation devices such as IoT clinical devices.

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