A NOVEL NEURAL EEG DECODING FOR STRESS DETECTION USING OPTIMIZED GATED RECURRENT NEURAL NETWORKS

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Abstract:
Electroencephalography (EEG) is a non-invasive method used to record evoked potentials and electrical activity from the brain. Recently, Artificial Intelligence particularly machine learning (ML) and deep learning (DL) has gained brighter light of research for analyzing the different EEG patterns. Furthermore, decoding of stress from the EEG patterns using ML and DL algorithms is considered as the one of the brightest light of problem that remains challenge among the researchers. In this context, this paper proposes the Modified Gated Recurrent Neural networks (M-GRU) with the Optimized training neural network to decode the stress from EEG patterns with high accuracy and less computational complexity. The proposed GRU networks are used to extract the temporal features while the optimized learning models are used for the complexity free classification and detection which can be used for the further treatment and diagnosis process. The extensive experimentation is carried out using the PhysioBank EEG Stress datasets and various performance metrics such as accuracy, precision, recall, specificity and F1-score are calculated and compared with the other state-of -art learning models. Simulation results shows that the proposed algorithm has shown the better performance than the existing models and has gained the substantial attention in decoding EEG signals for stress detection.

Keywords: EEG patterns, Artificial Intelligence, Modified Gated Recurrent Neural Networks, Optimized Training networks, Stress Decoding.
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1. Introduction

The human brain is a complex system containing approximately 100 billion neurons and trillions of synaptic connections [1,2]. The brain's electrical activity became a research focus in the 19th century when Richard Caton recorded brain signals from rabbits [3,4]. Brain recordings were also performed by Hans Berger, the first person to record electroencephalogram (EEG) signals from the human scalp [5]. EEG-based research has since increased significantly, and EEG is now the most commonly used non invasive tool to study dynamic signatures in the human brain [6,7]. EEG signals measure voltage fluctuations at the scalp and reflect the instantaneous superposition of electric dipoles, primarily from dendritic inputs to large pyramidal cells in the neuropil [8]. Signals traveling in white matter have traditionally been thought to be too fast to superimpose temporally, although recent cable theoretic models [9] and empirical work [10] suggest that white matter may also contribute to brain rhythms measured at the scalp. The brain waves are most commonly used in EEG signal analysis for different activities as shown in Figure 1. Hence, decoding EEG favors more attraction in designing the Stress Detection System (SDS) in which the stress is considered as the one of thrust problems in recent times.

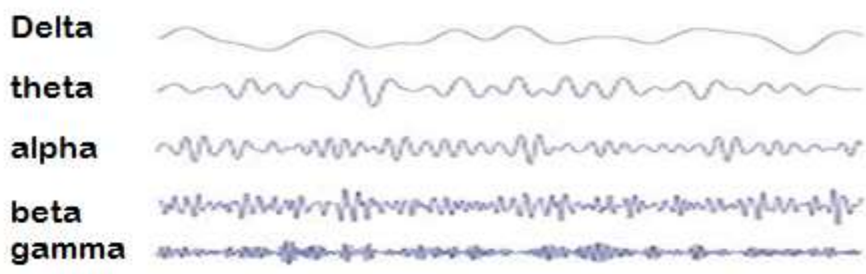

Figure 1 EEG with different frequency rhythms

In recent time, advent of machine learning (ML) and deep learning (DL) algorithms has thrown the bright light in designing the EEG based SDS. Many algorithms such as Support vector machines [11], Deep neural Networks (DNN)[12], Long Short term Memory (LSTM)[13] are used for developing an efficient stress detection system. However, these methods need the improvisation in terms of high stress detection and less computational complexity. To overcome this above problem, this paper proposes the complexity aware Gated Recurrent Units (MGRU) with Optimized Neural Networks to get the better accuracy for the multiple datasets. To best of our knowledge, the proposed network is first of its kind to handle the multiple stresses to achieve the better classification accuracy.

Contribution of the paper:

1. The paper proposes the novel Modified GRU network in which the traditional dense layers are replaced with optimized dense layers to achieve the better classification and reduced time complexity.
2. The Ant-Lion optimization algorithm is introduced as the optimization algorithm in the place of traditional optimizers such as ADAM and SGD optimizer.
3. The performance of the proposed network has been evaluated using the PhysioBank EEG stress datasets and compared with other existing learning based EEG-SDS.

Organization of the paper:
The rest of the paper is organized as follows: Chapter II presents the related works proposed by more than one authors. The working mechanism of the proposed framework, data collection unit, data preprocessing technique, proposed models are presented in Chapter-III. The experimentations, results, findings and analysis are presented in Chapter-IV. Finally the paper is concluded in Chapter-V with future enhancements

2. Related Works

Richa Gupta presented mental stress detection using EEG signals with the help of fusing 5 algorithms to increase the accuracy. For preprocessing of EEG signals, Normalized Least Mean Square (NLMS) is incorporated. The Discrete Cosine Transformation is adopted for feature extraction. The Modified Binary Particle Swarm Optimizer is incorporated for selection of EEG from the noisy environment. This framework utilized Whale optimized Support Vector Machines for the classification of EEG signals. This framework gives better results for stress level detection and classification by achieving better accuracy (96.36%), sensitivity (96.84%), specificity (90.8%) and F1 score (97.96%). This framework helps the psychiatrists for the sets level diagnosis. But this framework speed is degraded when noise present in the EEG signal are increased [14].

A. Hag presented a minimum redundancy maximum relevance with particle swarm optimization and support vector machines (mRMR-PSO-SVM) to select optimal features from the EEG signals. mRMR is plays an important role in the reduction of search space of the local optima. The PSO optimized SVM evaluates the ranked features selection and complete the stress level classification. This framework produced better results in terms of accuracy when compared with other models such as EDMSS, DEAP, SEED, and EDPMSC. The feature vector space is also reduced by the proposed framework and improvised the overall performance. But downside of this framework is, this framework lead to computational complexity under real time dataset [15].

A. Sundaresan investigated different ML classifiers for stress detection using EEG signals. This framework addressed 4 conventional Brain Computer Interface and 7 deep learning strategies for stress detection. Finally this framework concluded that LSTM RNN framework produced 93.27 % of accuracy for stress detection when compared with other techniques. Also suggested that this framework is more suitable for mental stress mitigation via the respiration entrainment adoption. However this framework leads to resource complexity and require more training time for large dataset [16].

L.V. Sharma presented whale optimized SVM approach for the detection and classification of stress detection. Within short duration this framework predicts the level of stress. The stationary wavelet transform is utilized for the decomposition of features which were significantly extracted from the EEG signals. The whale optimization is incorporated to optimize the weights of SVM strategy which results in 97.2559 % of accuracy. So this framework has the potential to detect the level of stress within the short duration hence it is proving highly reliable technique. But disadvantage of this framework is it require improvisation to handle real time datasets [17].

Attallah, Omneya provided deep investigation on stress level with the help of 36 participants. This framework established hybrid feature set for the classification of stress and non-stress states. In order to provide efficient stress level detection performance this framework reduced no. of electrodes utilized and place in various places on scalp and chosen the best signal for the experimentation to provide high accuracy. To reduce the computational complexity in the framework the Principle Component Analysis technique is incorporated which reduced the no. of features and provided optimal feature among all. From the findings it is shown that this framework achieved better results in terms of specificity (99.94 %), precision (99.94%) and accuracy (98.48%). But main constrain of this framework is it leads to time complexity when processing huge data in same time [18].

B.S Jawharali developed ANN based classification for stress level classification and to filter out the EOG artifacts from the Raw EEG signals which results in diminished classification error.

This framework is completely implemented using MATLAB simulation environment. This framework utilized time domain features and ensured the increased accuracy when contrasted with other methodologies. But limitation of this framework is exclude spatial domain features for the stress level detection hence required implementation to focus more features for the improved results [19].

B.Ramani discussed various ML algorithms for the detection of stress levels. This framework also covered different features extracted for the classification of EEG signals. Different features are extracted from the heart rate, skin conductance and difference in heart rate which are highly helpful for the stress level detection. Mainly powerful ML algorithm such as SVM, KNN, and Random Forest (RF) are discussed with its pros and cons. This framework cleared the importance of physiological signals in detecting the stress level. The main constrain found in this framework is many participants utilized various features that were associated with each other, which results in increased computation time. In addition to that, few of them utilized highly expensive instruments for the EEG signal extraction instead of low cost sensors [20].

O.AlShorman applied the front facing flaps EEG range investigation is applied to distinguish mental pressure. At first, these structures apply a Fast Fourier Transform (FFT) as a component extraction stage to quantify all groups' power thickness for the front facing projection. From that point forward, these systems utilized two kinds of characterizations like subject wise and blend (mental pressure versus control) utilizing SVM and Naive Bayes (NB) AI classifiers. The got consequences of the typical subject wise order showed that the proposed procedure has better precision (98.21%). In addition, this method has low intricacy, high precision, straightforward and simple to utilize, no over fitting, and it very well may be utilized as an ongoing and ceaseless observing procedure for clinical applications [21].

T. Lakshmi Prasanthi acquainted with the most common way of handling signals as per AI calculations: this system have utilized regular information gathered, for example, Respiration, GSR Hand, GSR Foot, Heart Rate, and EMG, from different examinations in an assortment of circumstances and regions while driving. From that point forward, the information division at various times, like 100, 200 seconds, and 300 seconds, was done any other way. This structure eliminated the numerical highlights from the isolated information and took care of these elements into the accessible separator. Likewise, used KNN, K's nearest neighbor, and a vector support machine, which is totally different. This structure isolated the strain into three levels: low, medium, and high. The outcomes show that the tension level can be reached with an exactness of 98.41% in 100 seconds and 200 seconds all the while and close to 100% with a period time frame seconds [22].

K. R. Pathak executed EEG channels and groups for include extraction and characterization calculations on benchmark DEAP (Dataset of Emotion Analysis for Physiological sign) dataset. This system talked about original element extraction calculations for human feeling of anxiety identification. This structure executed a computerized pressure acknowledgment framework utilizing Neurosky single-channel gadget. This structure carried out the programmed notice framework, on the off chance that pressure passes the boundary esteem sends the programmed warning, so can make a preventive move. Be that as it may, primary disadvantage of this system is its computational expense is too high [23].

3. Proposed Methodology

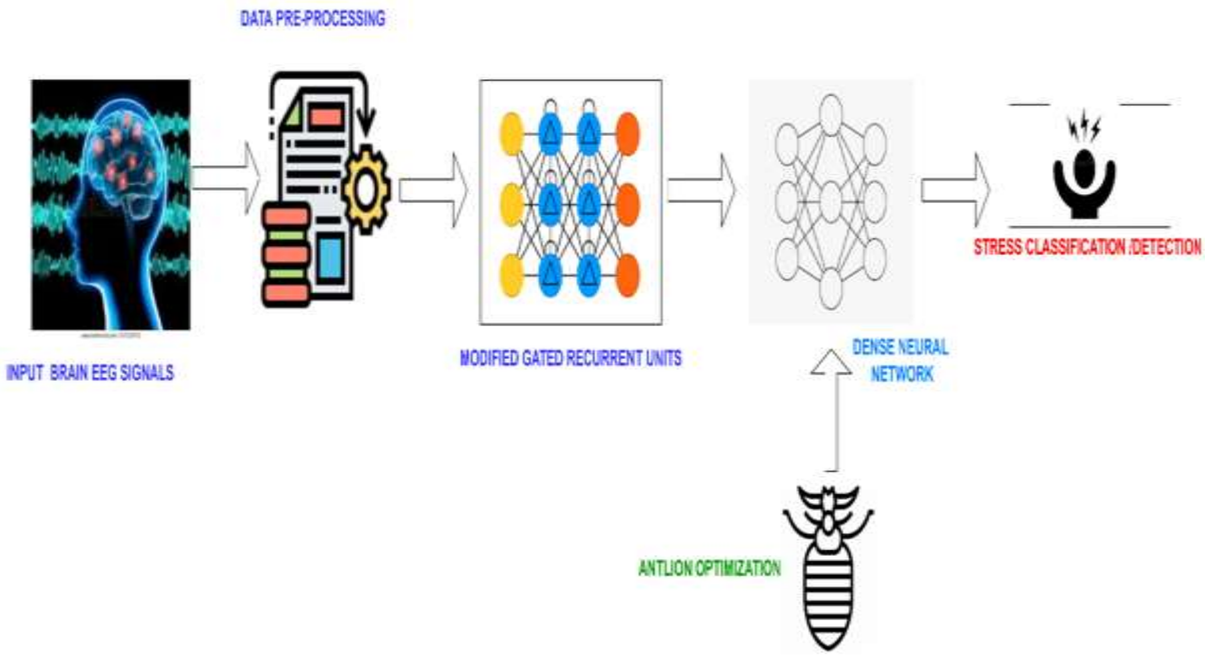

Figure 2 Overall Architecture for the Proposed Deep learning Framework

3.1 System overview

The proposed framework has three main phases,namely (i) Data collection and pre-processing and filtering (ii) Modified GRU based Feature Extraction (iii) Classification (Stress) . The block diagram of the proposed framework is shown in Figure 2

3.2 Materials and methods

EEG signals from physio bank [24] are used as the main source for data set collection. This dataset consists of EEG records of 36 subjects using the 10-20 international system. This data was recorded while performing cognitive mental workload; in this case, it is a complex serial subtraction. It contains 19 channels Anterior frontal (Fp1,Fp2), Frontal (F3,F4,F7,F8,Fz), Central (C3,C4,Cz), Parietal (P3,P4,Pz), Temporal (T3,T4,T5,T6) and Occipital (O1, O2) with the sampling rate of 500Hz. Every recording includes artifact free EEG of 182sec for baseline state and 62sec for task performing state, which is a stressed state.

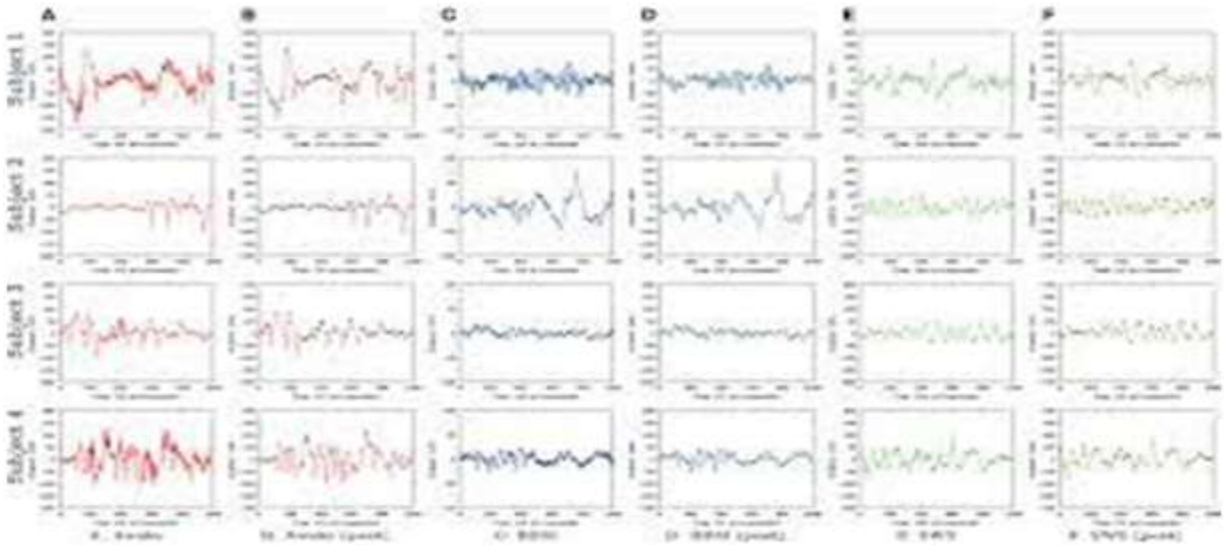

Figure 3 Sample EEG Signals From the PhysioBank used for Evaluation

3.3 Data pre-processing technique

In biomedical signal processing, the determination of noise and artifacts in the acquired signal is necessary to move to the feature extraction phase with a clean signal and achieve good classification results. For the aim of denoising and artifacts , this paper employs the MNE-python based libraries[36] to filter the relevant sub-bands of EEG signals. removing baseline we have applied an python and MNELAB script serving to cut relevant sub-band of EEG signals, removing baseline and removing Ocular and 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

3.4 Proposed classifier

3.4.1 *Optimized gated recurrent units (O-GRU):*

The most important structure used for the temporal feature extraction is GRU module, which receives the data collected from the IoT-cloud systems. Figure shows the structure of the GRU network used in the paper. GRU network consists of two gates and considered faster than LSTM and RNN models[25].

Where xt is the input feature at the current state , yt is the output state , ht is the output of the module at the current instant, Zt and rt is update and reset gates, W(t) is weights,B(t) is bias weights at current instant. The mathematical expression for the extracting the feature maps is given by

$$P = GRU(\sum_{t=1}^{n} \quad [x_{t,} h_{t,} z_{t,} r_t \big(W(t), B(t), \eta(tannh)\big)] \qquad (1)$$

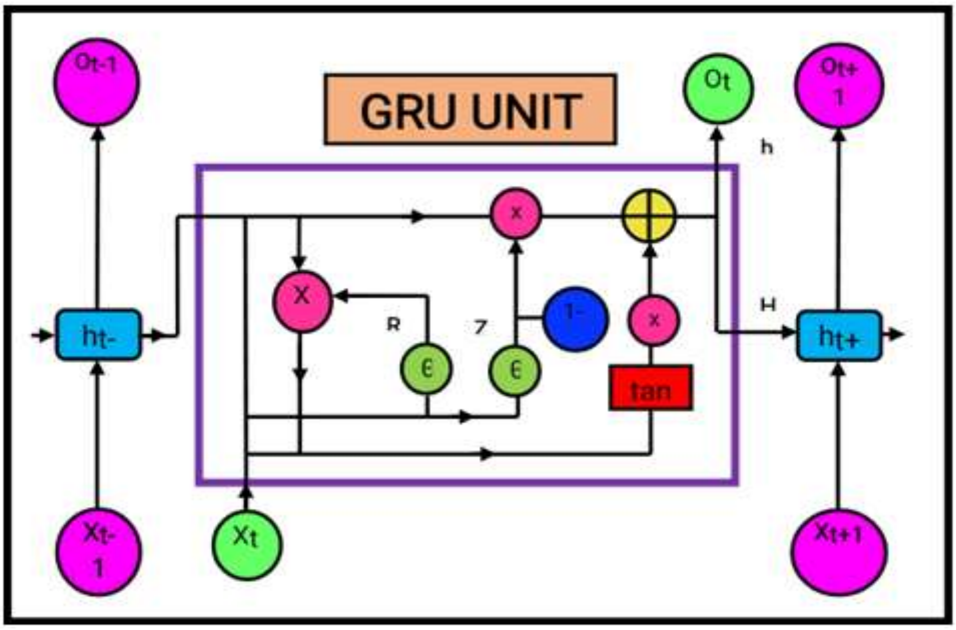

Figure 5 Architecture of the GRU used for the Feature Extractor

The GRU with dropout layers are used to learn the temporal features of pre-processed EEG signals and these features are used to train the classification layers of model. The proposed model replaces the traditional dense layers with optimized neural networks based on Ant-lion principles to increase the high accuracy with less computational complexity. These networks are trained with the hyperparameters such as epochs, input weights and bias factors .Hence to achieve the better classification ration of stress, above mentioned parameters are optimized to reduce the complexity which in turn increase the accuracy. The working principle of Ant-Lion optimization used in GRU network is discussed below.

Antlion optimization algorithm was proposed for the optimizing the hyperparameters in the networks.In nature, insects move indiscriminately in look for food. This stochastic development of insects over the hunt space is numerically demonstrated by utilizing aggregate total capacity and an arbitrary capacity applied over various cycle. Insects move over the inquiry space and antlions chase them and become fitter utilizing traps. Such arbitrary conduct power to track down the worldwide streamlining arrangement rather traps in neighborhood maxima. To evaluate wellness of each, a target work is utilized during streamlining. The objective function is a capacity used to communicate the real objective of the model as for amplify the use of assets in an effective manner. Additionally, this is likewise utilized as set of factors which control the Objective function wellness esteem. To apply this some supposition that is additionally made: In ALO, it is expected that the antlions likewise conceal some place in the pursuit space. Search space is confined by min max calculation. The ALO calculation reproduces five significant tasks of chases in hatchlings: arbitrary stroll of insects, building traps, entanglement of subterranean insects in traps, Sliding insects towards antlion, getting preys and re-building traps. These tasks might be demonstrated numerically as follows:

3.5.1 Random walk of ants

It's a moving assignment to track down the best calculation for such kind of arbitrarily modifiable issue. Insects change their areas with subjective stroll at each progression of enhancement. Taking into account the way that each search space is limited for example has a limit, so for this explanation, the discretionary stroll of insects is confined inside the limits of search space by utilizing min–max standardization.

3.5.2 Building traps

To entangle the prey (i.e Ant), Antlion makes a trap (i.e pit) .The external edge of the pit is sharpe to the point that empowers to tumble down the metallic subterranean insect effectively in to down of the pit. The profundity of the pit is up to 1cm to 3cm, relies on their craving conduct.

The chasing instrument of antlion is displayed by utilizing a roulette wheel in which there are higher possibilities for the choice of a fitter antlion to get the subterranean insects. It is accept that the insects are caught in just one chose antlion.

3.5.3 Entrapment process

Antlion is plunk down of the pit and hanging tight for the prey. ALO utilizes an administrator that is roultte wheel. Roullte wheel is an administrator is utilized for choosing the antlion dependent on their wellness esteem. Insect Lions burrow their pits corresponding to their wellness worth to get the prey.

3.5.4 Sliding ants towards antlions

At the point when an insect is in a snare, the antlion begins tossing sands outwards the focal point of the pit to slide down the getting away from insect. To numerically display this progression the sweep of subterranean insects' irregular strolls hyper-circle is diminished adaptively.

3.5.5 Catching prey and rebuilding

In the long run, an insect is trapped in the antlion's jaw when it is slipped to the lower part of the pit. This cycle of getting prey is mimicked by expecting that the subterranean insect has gotten fitter than its relating antlion. From that point the antlion refreshes its situation to the latest situation of the pursued insect to improve its probability of getting new prey.

3.5.6 Elitism

Elitism protects the best solution(s) got during every age and here the fittest antlion accomplished as of recently in every emphasis is saved and considered as a world class antlion. Presently this world class antlion impacts the developments of the multitude of subterranean insects during cycles. The developments of insects are additionally impacted by the subjectively picked antlion by the roulette wheel all the while. Elitism is an imperative apparatus for such sort of developmental calculation to tracking down the best arrangement at any phase of streamlining measure.

3.5.7 Mathematical model for antlion optimization

In search space, a random walk is utilized to model the stochastic move of ants which is represented as follows

$$X(t) = [0, cumsum(2r(t_1) - 1), umsum(2r(t_2) - 1), \ldots \ldots \ldots . umsum(2r(t_n) - 1) \quad (10)$$

Where
X(t) □ ant random walk,
n □ maximum number of iteration,
t □ current iteration,
cumsum□ cumulative sum
r(t) □ a stochastic function which is represented as follows

$$r(t) = \{1 rand > 0.5 0 otherwise \quad (2)$$

where
rand □ random number in the interval of [0; 1].
Ants and antlions positions is given by the following matrices

$$M_{Ant} = \left[A_{1,1} A_{1,2} \cdots A_{2,1} A_{2,2} \cdots \vdots \vdots \vdots \quad \cdots A_{1,d} \cdots A_{2,d} \vdots \vdots \; A_{n,1} A_{n,2} \cdots \cdots A_{n,d}\right] \quad (3)$$

$$M_{Antlion} = \left[AL_{1,1} AL_{1,2} \cdots AL_{2,1} AL_{2,2} \cdots \vdots \vdots \vdots \quad \cdots AL_{1,d} \cdots AL_{2,d} \vdots \vdots \; AL_{n,1} AL_{n,2} \cdots \cdots AL_{n,d}\right] \quad (4)$$

where
M_{Ant} matrix that saves ant position,
$M_{Antlion}$□ a matrix that saves antlion position,
A_{ij} gives the i-th ant value at the j-th dimension,
n □ No. of ants
d □ No. of dimensions
To evaluate each ant and antlion, a fitness function is used and the results is stored in matrix and which is given as follows

$$M_{OA} = \left[f([A_{1,1} A_{1,2} \cdots f([A_{2,1} A_{2,2} \cdots \vdots \vdots \vdots \quad \cdots A_{1,d}]) \cdots A_{2,d}]) \vdots \vdots \; f([A_{n,1} A_{n,2} \cdots \cdots A_{n,d}])\right] \quad (5)$$

$$M_{OAL} = \left[f([AL_{1,1} AL_{1,2} \cdots f([AL_{2,1} AL_{2,2} \cdots \vdots \vdots \vdots \quad \cdots AL_{1,d}]) \cdots AL_{2,d}]) \vdots \vdots \; f([AL_{n,1} AL_{n,2} \cdots \cdots AL_{n,d}])\right] \quad (6)$$

where
MOA □ant fitness matrix,
MOAL □ antlion fitness matrix,
$A_{i,j}$ gives the i-th ant value at the j-th dimension,
n □No. of ants,
f □ objective function.

To keep ants random walk inside the search space, the following expression is used to normalize ant position.

$$X_i^t = \frac{(X_i^t - a_i)(d_i^t - c_i^t)}{b_i - a_i} + c_i^t \quad (7)$$

where a_i, b_i□ minimum & maximum random walk of i-th variable respectively,
c_i^t, d_i^t□ minimum & maximum of i-th variable at iteration t.
to model the behaviours of antlions' trap, the following expressions are utilized

$$c_i^t = Antlion_i^t + c^t \qquad (8)$$

$$d_i^t = Antlion_i^t + d^t \qquad (9)$$

$$c^t = \frac{c^t}{I} \qquad (10)$$

$$d^t = \frac{d^t}{I} \qquad (11)$$

Where

c^t; d^t□ minimum & maximum of all variables at t-th iteration respectively,
c_i^t, d_i^t□ Minimum & maximum of all variables for i-th ant respectively,
$Antlion_j^t$ Shows the j-th antlion position at t-th iteration,
I □ sliding ratio changes which is expressed as follows

$$I = \begin{cases} 1 + \frac{10^6 iter}{MaxIter} & if \quad 0.95MaxIter < iter < MaxIter \\ 1 + \frac{10^5 iter}{MaxIter} & if \quad 0.90MaxIter < iter < 0.95MaxIter \\ 1 + \frac{10^4 iter}{MaxIter} & if \quad 0.75MaxIter < iter < 0.90MaxIter \\ 1 + \frac{10^3 iter}{MaxIter} & if \quad 0.5MaxIter < iter < 0.75MaxIter \\ 1 + \frac{10^2 iter}{MaxIter} & if \quad 0.1MaxIter < iter < 0.50MaxIter \\ 1 & otherwise \end{cases} \qquad (12)$$

The best solution (antlion position) termed as R_E^t is saved and the fittest antlion affect all ants movements. R_A^t is an antlion selected by roulette wheel as in the following equation:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \qquad (12a)$$

To model the final hunting stage when the ant is pulled inside the sand and being consumed. Then, antlion update its position according to the next equation:

$$Antlion_i^t = Ant_i^t \, if (Ant_i^t) < Antlion_i^t \qquad (13)$$

3.5 Antlion optimized GRU training layers

To optimize the hyperparameters such as no of epochs, bias weights, hidden layers , ant lion optimization algorithm is used for the proposed training network. The fitness function is calculated using the mathematical expression (14).

$$FitnessFunctionF\big(A(GRU)\big) = (1 - A(x)) \qquad (14)$$

Where A is the maximum accuracy .The fitness function is calculated at each and every iteration and checks it meets the threshold. The pseudo code for the optimization of network is presented in Algorithm-1 the optimized parameters obtained for the proposed architecture to achieve the higher accuracy is shown in Table I

Table I Parameters for Training the GRU Learning Networks after Optimization

S.no	Parameters	Optimized Parameters
01	No of Epochs	100
02	Learning Rate	100%
03	No of batches	32
04	Optimization Iterations	20
05	No of hidden nodes	200

4. Results and Discussion

The complete algorithm developed using TensorFlow 2.1 with Keras as Front End and implemented in the PC workstation with NVIDIA GPU,256 SSD, 8GB RAM and 3.2 GHZ operating frequency. Table II presents the mathematical expression for performance metrics such as accuracy, precision, recall, specificity and F1-score used for evaluating the proposed network. Higher scores of the metrics indicate the better performances. To solve the network's overfitting problem and improve the generalization problem, early stopping method is used in the paper. As discussed in Section 3.1, more than 15000 datasets were collected in which the 70% is taken as training and 30% as testing.

Table III Mathematical Expressions for the Performance Metrics' Calculation

S.No	Performance Metrics	Mathematical Expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Recall	$\frac{TP}{TP+FN}$ x100
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison * Recall}{Precision + Recall}$

TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is False negative values. The performance metrics of the proposed algorithm is calculated using the above mathematical expressions as mentioned in table II. To prove the superiority of the proposed algorithm, performance is compared with the other state-of -art deep learning algorithms. Table III shows the performance metrics of the different algorithm in detecting the stress from the preprocessed EEG signals.

Table III. Comparative Analysis of the Different Algorithms in detecting the Stress from EEG Signals

Algorithms	Performance Metrics				
	Accuracy	Precision	Recall	Specificity	F1-score
BI-LSTM	0.89	0.851	0.875	0.856	0.867
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	0.988	0.9873	0.9883	0.0123	0.993

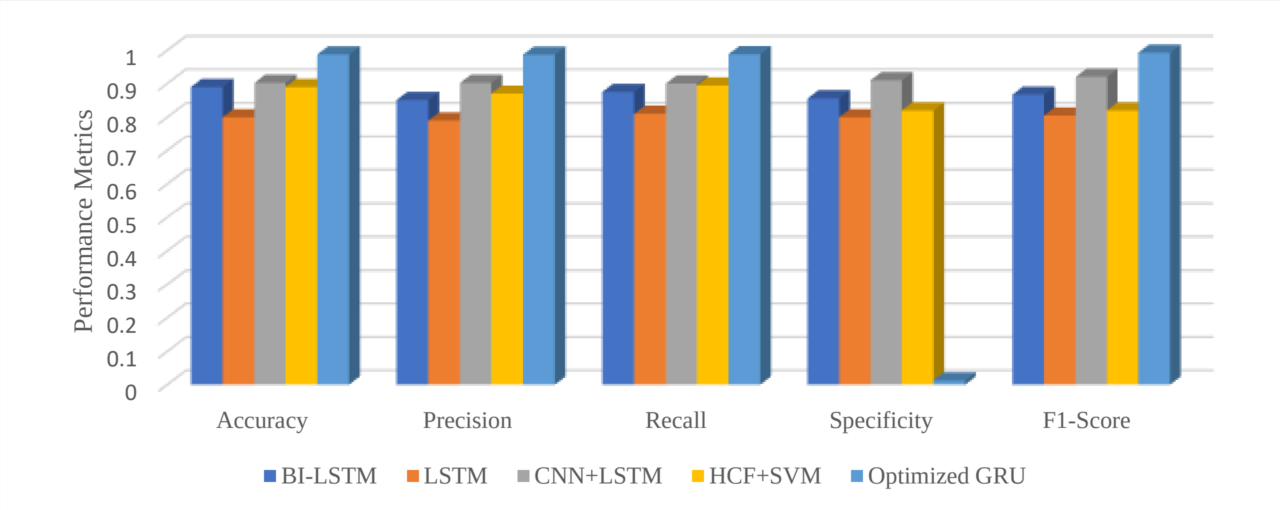

Figure 6 Comparative Analysis of the Different Algorithms In Stress Detection mechanism

Table III and Figure 6 presents the comparative analysis between the performances of proposed and existing algorithms. From the above figure and table, it is found that the proposed model has outperformed the other existing learning in terms of accuracy, precision, recall, specificity and recall. The integration of optimized learning machines with GRU network has proved its excellence over the other existing algorithms.

5. Conclusion and Future Scope

This main goal of the research is to detect and classify the stress from EEG using Ant Lion optimized GRU networks. To classify the stress from the EEG stress data, GRU is used as the feature extractor layer and dense layer is replaced with Ant Lion Optimized classification layers that are used to train the network to achieve the better stress detection and classification. The experimentation is carried out using the PhysioBank EEG datasets. The collected EEG signals are preprocessed, filtered and given as the input to the proposed model. The proposed GRU is used to extract the features which are then fed as input to the Ant-Lion optimized dense layers for further classification of EEG Stress from Human. The proposed algorithm was developed using Tensorflow 2.1 with Keras API and compared with other existing hybrid architectures. The results show that the proposed architecture has outperformed the other state-of art architectures. As the future enhancement, the proposed algorithm needs more improvisation in terms of the handling the versatile and real time clinical datasets.

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