Journal of Scientific & Industrial Research
Vol. 83, November 2024, pp. 1184-1193
DOI: 10.56042/jsir.v83i11.12298

Gradient One-to-One Optimizer and Deep Learning based Student Stress Level Prediction Model

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Received 06 July 2024; revised 27 August 2024; accepted 29 September 2024

Student stress-based issues are considered as the most common reason in the student environment. Student stress level prediction is the major source for students' academic performance and health. Students' stress levels increase the prevalence of psychological as well as physical challenges like nervousness, anxiety, and depression. Over the past years, different machine learning and deep learning based models have been proposed for student stress level prediction but they suffer certain limitations such as complex structure, less efficiency, high chance of misclassification, high chance of making mistakes. Predicting stress levels at early stage may help to minimize its impact and various serious health problems pertaining to this mental state. For this, automated frameworks are needed to predict stress levels accurately. This study proposes a hybrid approach named as GOOBO: DSNN (Gradient One-to-One Based Optimization: Deep Spiking Neural Network), that may identify stress accurately and efficiently utilizing optimization based hybrid of deep learning techniques. Here, the GOOBO is designed by incorporating Stochastic Gradient Descent (SGD) and One-to-One Based Optimization (OOBO). Here DSNN has been used which uses spiking neurons having different learning dynamics compared to traditional artificial neurons. Here proposed stress prediction model's effectiveness has been enhanced by bio-inspired nature of DSNN simulating biological neural systems. The performance of the proposed GOOBO-DSNN is analyzed for its effectiveness using evaluation metrics such as accuracy, sensitivity, specificity, and precision. The proposed GOOBO-DSNN attained the maximum accuracy, sensitivity, specificity, and precision as compared to recently developed models. The proposed GOOBO-DSNN accomplished the higher accuracy, sensitivity, specificity, and precision of 90.976 %, 91.698 %, 91.336 %, and 90.179 % respectively. Duplicate attributes have been deleted, and missing values are filled in during the preprocessing step of the dataset.

Keywords: Deep spiking neural network, Lorentzian similarity, One-to-one based optimization, Stochastic gradient descent, Stress level prediction

Introduction

Stress does not come under psychiatric diagnosis; nevertheless, it is further related to the mental wellbeing circumstances together with post-traumatic stress disorder, psychosis, anxiety, and depression. Stress may be described as, "The inability to cope with a perceived threat to one's mental, physical, emotional, and spiritual well-being which results in a series of physiological responses and adaptations".[1] This threat may take two forms: positive, like graduating or beginning a new relationship, or negative, also termed as distress: such being placed on academic probation or not having enough money for semester fees.[2] As one of the most frequent causes of common health issues, stress must be identified early and continuously monitored in order to create effective interventions and treatment options. The unexpected shift to isolated learning forced students to seriously be contingent on mobile applications. The mental well-being of students has been negatively impacted by isolation and a lack of social prospects, which has resulted in sentiments like sadness and loneliness.[3,4] The main cause of the rise in stress among learners in college is this.[5] Every day, many students commit suicide in different parts of the country.[6] Students are frequently overworked and overburdened with exams, papers, and part-time jobs,

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in today's competing and challenging scenario. Long-term exposure to challenging educational and social environments can lead to decreased immunity, changes in memory and cognition, brain abnormalities, as well as cardiovascular disease, and poor academic performance.[7] The experiments show that stress enhances the illness psychologically, and affects a diverse range of physical, vulnerability to infection, and behavioral conditions, like sleep disorders, depression, and anxiety. Furthermore, high levels of stress, which are common in today's world, can have a detrimental impact on general wellbeing and work productivity.[8] Identifying the factors of mental health problems among students has become a challenging task.[9]

Teachers can learn more about the academic development of each student by examining a variety of characteristics, such as involvement, attendance, study habits, and grades. With the use of this information, they may better adapt their teaching strategies to each student's unique needs, resulting in a more successful and individualized learning environment. Teachers can address issues and assist students in realising their full potential by spotting patterns and trends in student performance and acting accordingly. However, it is challenging to predict a student's performance with any degree of accuracy due to the complexity of human behaviour and learning patterns. Prediction accuracy can also be impacted by variations in data quality as well as availability. In spite of these issues, the accuracy and efficacy of student performance projections can be increased by the developing more powerful predictive models and constant refinement of data collection techniques. One potential obstacle, though, may be the current models' limited adaptability to various educational environments and student demographics. For the models to be widely used and have an impact, it is imperative that they be effective and flexible in a variety of situations.[10] Many experiments present that the ML technique shows tremendous potential ability to define stress levels, moreover, there are some of the challenges presented in predicting stress tasks, adding up, data irregularity, cold start challenge, and inter-subject variability that make previous technique ill-suited to this task. Deep learning techniques are used to give solutions to similar stress level balancing challenges.[11] Haque *et al*.[12] presented an extensive examination of 43 studies documenting the application of different Artificial Intelligence (AI) techniques in order to discover successful approaches imposed to the collecting, processing, and predicting stress from HRV (Heart Rate Variability) data. Rodrigues & Correia[13] in their research work aimed to provide an alternate strategy to identify stress in the workplace without requiring special controlled settings by utilising technical advancements that allow for the non-invasive collection of stress-related data. Sourkatti *et al*.[14] utilised machine learning to categorise the subjective emotional state after tasks that were pertinent to daily life. Dhariwal *et al*.[15] suggested a methodology which presents a way for understanding and assessing the frequency of neurological illnesses that is based on AI. Sadruddin *et al*.[16] provides a comprehensive review of wearable sensor-based and machine/deep learning-based stress detection strategies. Numerous machine learning methods have been used to analyse data and identify stress, including Logistic Regression (LR), Support Vector Machines (SVM), Random Forests (RF), and deep learning frameworks. Objectives of the study by Dickhäuser *et al*.[17] were to investigate the function of emotional distress in a transactional model (influenced by Lazarus' transactional stress model) and to replicate earlier findings using the demand-control model. Several types of other characteristics, including mental health, stress, demands as well as control, were evaluated. Ramachandra *et al*.[18] proposed a model which sends personalised alert messages to people according to how stressed they are, so they can get help and intervention right away.

In this framework the new approach GOOBO-DSNN is developed for student stress level prediction. Here, the input data is taken from the database, and is allowed for data normalization by employing the log scaling method, and the normalized data is allowed for feature selection using Lorentzian similarity. Finally, the selected features are subjected to student stress level prediction using DSNN and the weights of DSNN are fine-tuned using the developed GOOBO algorithmic approach. Here, the GOOBO is designed by incorporating SGD and OOBO.

The developed GOOBO-DSNN contribution is explicated below:

Designed GOOBO-DSNN for Students' Stress Level Prediction: A novel model called GOOBO-DSNN is defined for students' stress level prediction.

The developed GOOBO-DSNN is attained by incorporating the SGD and OOBO and is used to train the hyperparameters of the DSNN.

Literature Survey

Different researchers have proposed different models for stress level prediction using Machine Learning and Deep Learning Techniques, some of them are discussed below with their merits and limitations.

Parthiban *et al*.[1] designed an approach based on Support Vector Machine (SVM) for Mental Stress of Young Students prediction. This approach effectively examined the contextual information by correctly classifying classes under low error rates for contrasting and predicting the young student's mental stress. However, this technique was not suitable for real-time prediction of student stress levels and it failed to consider nearby neighbors for executing the prediction task. Rois *et al*.[2] developed a Random Forest (RF) approach with low standard error and low value of uncertainty while predicting stress among students for increasing the prevalence rate of stress. Moreover, it failed to utilize the LR (Logistic Regression) model to overcome multicollinearity problems that generate misleading results while predicting the prevalence of stress. Luo *et al*.[3] devised a technique called Cross-personal Activity Long Short Term Memory (LSTM) Multitask Network (CALM-Net) that was highly effective and reliable in stress levels predicting without utilizing any personalized parameters and addressed cold-start and inter-subject variability issues during stress prediction. Nevertheless, it failed to potentially ensure scalability together with maximized security and privacy for a practical stress prediction process. Ratul *et al*.[4] implemented a method for stress level prediction called Evolutionary-Genetic Algorithm (GA) + Multi-Layer Perceptron (MLP). This method attained less computational time, low dimensionality while detecting most members qualified medium to low-level social as well as high to medium-level psychological stress. This technique failed to explore the effect of access to resources, and socioeconomic status like mental health treatments and fast internet, on stress levels and academic performance. Anand *et al*.[5] developed a Decision Tree + Random Forest + AdaBoost classifier (DT+ RF + AB) approach for reliable stress level classification, further reducing the overfitting issues that occur while predicting students' stress levels thereby leading to a reduction in stress levels and improving academic lifestyle. Nevertheless, this technique did not analyze the pattern of the responses in various classes regarding stress level and it was not successful in devising a personalized assistant wherein every student can submit values for all attributes.

The prevailing techniques maximized the effectiveness of the result for stress levels prediction and defining a student's daily habits and eliminates workload to living a stress-free student life. However, these techniques had limited generalizability, limited data samples are the common challenges.

Proposed GOOBO-DSNN for Student's Stress Level Prediction

To overcome the above challenges, the proposed technique is implemented. At first, the input medical student's mental health data from the database is gathered. Then, the input mental health data is allowed for data normalization using the log scaling method[19] and the normalized data is allowed for feature selection using Lorentzian similarity.[20] Finally, the selected features are subjected to student stress level prediction using DSNN[21], and the weights of DSNN are fine-tuned using GOOBO algorithmic approach. Here, the GOOBO is designed by incorporating SGD[22] and OOBO.[23] The architecture of the introduced GOOBO-DSNN approach for student stress level prediction is presented in Fig. 1.

Data Acquisition

The input data considered for student stress level prediction is taken from the dataset[24] with amount of data, and it is denoted by the expression given below,

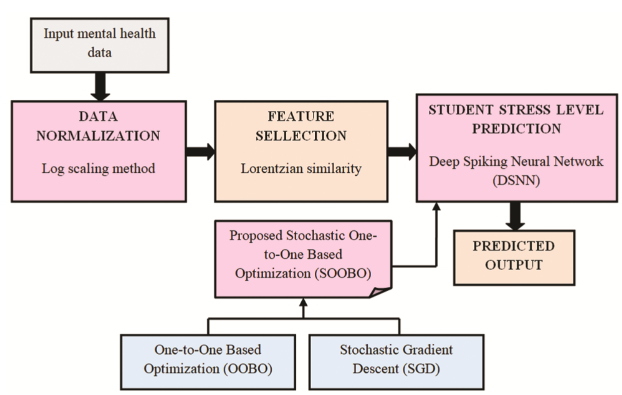

Fig. 1 — Block diagram of the proposed GOOBO-DSNN approach for student stress level prediction

$$T = \{T_1, T_2, T_3, ...T_a, ..T_m\} \quad \ldots (1)$$

Here, m represent the overall number of data, T_a represent the a^{th} data as well as it is applied for additional process, and T represent the input dataset.

Data Normalization

The input data T_a is normalized by employing log scaling.[19] Here, normalization is the procedure in the preprocessing stage as it reduces the dependency and redundancy, and also, the normalization can variant the numeric data into a particular range.

Log Scaling Normalization

Log Scaling is employed for data normalization to describe the arithmetic values on a non-linear scale, and this method is employed to transfer information by adding a logarithm function to the values, rather than linearly as in a linear scale. Here the log scaling is represented as,

$$R_d = \log(T_a) \quad \ldots (2)$$

Here, R_d represent the normalized data, T_a denote the input data.

Feature Selection

In feature selection, the normalized output R_d is further fed to the feature selection process, the feature selection process is accomplished by using the Lorentzian similarity.[20] Where, it is the process of reducing the quantity of input variable when demonstrating the predictive methods.

Lorentzian Similarity

In Lorentzian similarity, 1 is added to eschew the log of zero and assure the non-negativity property. In feature selection the Lorentzian feature is represented as,

$$L = \sum \ln(1 + |H_x - I_x|) \quad \ldots (3)$$

Here, L defines the Lorentzian feature, H_x is represented as data, I_x is signified as attribute, l_n denote the natural log. Feature selected using Lorentzian similarity is denoted as L_F.

Student Stress Level Prediction using DSNN with GOOBO

The feature selected using Lorentzian similarity L_F is further applied to the student stress level prediction using the DSNN.[21] The DSNN is the form of an artificial neural network that analyzes the biological neurons' behaviors with the help of a spiking neuron model, where the DSNN normally uses the process data and continuous activations in a continuous manner. Further, the DSNN has the advantages of energy efficiency, biological plausibility, temporal processing, and robustness to noise and so on. Here, the weights of DSNN are fine-tuned using GOOBO algorithmic approach where, the GOOBO is designed by incorporating SGD and OOBO.

Architecture of DSNN

The DSNN[25] is accomplished by combining both the CNN and SNN. Both the SNN and CNN have similar architecture. The major changes among CNN and SNN are the various forms of transfer data and input. Every data is the input to the classical CNN. Additionally, propagation between network layers is achieved in the SNN until certain numerical values are generated. However, for SNNs, the input is typically the signal sequence which signifies event flow. The SNNs accomplish the pseudo-simultaneity of output and input, as well as employ definite hardware for further effectual computing. In DSNN by training the CNN the network parameters are attained, in CNN the parameters trained are utilized and converted in to SNN layers. Moreover, during the conversion there may contain a particular transfer loss. So that both the SNN and CNN are need to employed to minimize the conversion loss. The student stress level predicted output is signified as F_G. The DSNN architecture is portrayed in Fig. 2.

Training of DSNN with GOOBO

The GOOBO employed for optimizing the structure of the DSNN is attained by merging the SGD and OOBO algorithms. The SGD is employed for reducing the loss function to enhance the technique parameters, where the SGD is effective because of the memory efficiency, generalization,

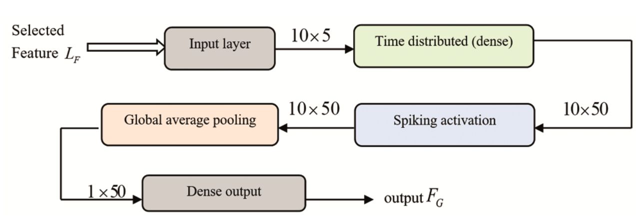

Fig. 2 — Block diagram of DSNN

scalability, and speed. The OOBO is the metaheuristic-based population algorithm that can present the effective result for the problems in optimization. The OOBO algorithm is effectual in handling the heterogeneous information and effective in handling the optimization problem.

Further, the GOOBO technique is detailed in below steps:

Step 1. Initiation

For each population member the OOBO algorithm is the solution for the given problem. Every population member can be depicted using a vector, and is depicted as,

$$\vec{B}_y = \left[B_{y,1}, ..., B_{y,e}, ..., B_{y,h}\right], y = 1, ...W \quad ... (4)$$

The population members are randomly located in the search space to generate the initial population as follows.

$$B_{y,e} = st_e + rand(), \left(kt_e - st_e\right), e = 1, ...h \quad ... (5)$$

Here, $\vec{B}_y$ is the y^{th} population member, $B_{y,e}$ denotes its e^{th} dimension, st and kt designates the lower and upper bounds of the problem space, h is the population size, $rand()$ represent the function making a random uniform number from the interval [0,1] and W signifies the population size.

Step 2. Fitness Function

The optimal outcomes are the one that has the least error which is measured with respect to Mean Square Error (MSE), and is described below,

$$MSE = \frac{1}{E}\sum_{n=1}^{E}\left(F_G^* - F_G\right)^2 \quad ... (6)$$

Here, the expected output is F_G^*, the output of DSNN is F_G and number of training samples as E.

Step 3. Population Update

All population members need to contribute in update of population. The random procedure of generating the group $\vec{J}$ of the locations of member guidance is defined by,

$$\vec{J} = \left\{\left[J_1, ..., J_{\updownarrow}, ..., J_W\right] \in H_{\bar{W}}; \forall \updownarrow \in \bar{W} : J_{\updownarrow} \neq \updownarrow\right\} \quad ... (7)$$

where, $\bar{W} = \{1, ..., W\}$, $H_{\bar{W}}$ is the set of all permutation of the $\bar{W}$ set, as well as $J_{\updownarrow}$ is the $\updownarrow^{th}$ element of the $\vec{J}$ vector.

In OOBO to guide the y^{th} member B_y, the population member position is $J_y\left(B_{jy}\right)$ in the population Matrix is selected, and the updation is carried out as follows,

$$B_{y,e}\left(z+1\right) = B_{y,e}\left(z\right) + rand(\ )\left(B_{J,e}\left(z\right) - YB_{y,e}\right) \quad ... (8)$$

$$B_{y,e}\left(z+1\right) = B_{y,e}\left(z\right) + rand(\ ) \cdot B_{J,e} - rand(\ ) \cdot YB_{y,e}\left(z\right) \quad ... (9)$$

$$B_{y,e}\left(z+1\right) = B_{y,e}\left(z\right)\left[1 - rand(\ )Y\right] + rand(\ )B_{J,e}\left(z\right) \quad ... (10)$$

where, the new suggested status $B_{y,e}\left(z+1\right)$ is the y^{th} member in the e^{th} dimension $B_{j,e}$ is the e^{th} dimensions of the J^{th} selected member to guide the member.

The training of the neural network with free parameters p can be represented as the challenge of reducing a function $g : \varpi^p \to \varpi$. The commonly employed procedure to optimize p is to iteratively adjust $B_y \in \varpi^p$ using the gradient information $\nabla p_y\left(B_y\right)$. The SGD 13 then changes an elaboration of gradient descent to stochastic optimization of the p as follow,

$$B_{y,e}\left(z+1\right) = B_{y,e}\left(z\right) - \beta\nabla g\left(B_{y,e}\left(z\right)\right) \quad ... (11)$$

where, β describe the learning rate, and ∇g designates the gradient of the parameter.

$$B_{y,e}(z) = B_{y,e}(z+1) + \beta\nabla g\left(B_{y,e}(z)\right) \quad ... (12)$$

Substituting equation (12) in equation (10),

$$B_{y,e}(z+1) = \left(B_{y,e}(z+1) + \beta\nabla g\left(B_{y,e}(z)\right)\right)\left[1 - rand(\ )Y\right] + rand(\ )B_{J,e}(z) \quad ... (13)$$

$$B_{y,e}(z+1) - B_{y,e}(z+1)[1 - rand\ (\ )Y\ ] = \beta \nabla g(B_{y,e}(z))[1 - rand\ (\ )Y\ ] + rand\ (\ )B_{J,e}(z) \quad \ldots (14)$$

$$B_{y,e}(z+1) = \frac{1}{rand\ (\ )Y}\left(\beta \nabla g(B_{y,e}(z))[1 - rand\ (\ )Y\ ] + rand\ (\ )B_{J,e}(z)\right) \quad \ldots (15)$$

Here, $B_{y,e}(z)$ represent the position of the population member in the z^{th} iteration.

Step 4. Feasibility Evaluation

The fitness of the updated solution is calculated, and the solution with the lower fitness is taken as the finest solution.

Step 5. Termination

Till the extreme number of iterations is obtained, the procedure is repetitive to obtain the ideal solution.

Experimental Setup and Simulation Results

The devised GOOBO-DSNN for student stress level prediction is analyzed with different metrics and is elaborated in this segment as well as its effectiveness is associated with further classical techniques. The implementation of the introduced GOOBO-DSNN is accomplished with the help of Python tool. The Medical Student Mental Health dataset[24] is used to predict stress levels among medical students. This dataset includes 886 samples, capturing key demographic details, self-reported information, and results from psychological assessments, providing a comprehensive overview of the mental health of students in the medical field. The features include a unique identifier for each student, age, year of study, gender, possible language-related scores or categories, participation status, employment status, weekly study hours, self-reported health status, psychological or psychiatric condition, job-specific performance evaluation, cognitive empathy score, affective empathy score, measures related to mood, stress, or psychological well-being, mean score for emotional regulation or recognition, anxiety levels (measured by the State-Trait Anxiety Inventory), cynicism score, and professional efficacy score. The developed GOOBO-DSNN model is accomplished with different approaches based on student stress level prediction to estimate its effectiveness. The methods chosen for comparison are RF[2], CALM-Net [3], GA + MLP [4], and the Ensemble model.[5] This section represents the examination of performance of the developed GOOBO-DSNN with the existing models regarding precision, specificity, sensitivity, and accuracy.

Evaluation Measures

The GOOBO-DSNN is assessed regarding metrics namely accuracy, sensitivity, specificity, and precision.

a) Accuracy

The ratio of the accurately detected outputs to the total samples applied to the GOOBO-DSNN is its accuracy and it is described below,

$$Accuracy = \frac{A_1 + M_2}{M_1 + A_2 + A_1 + M_2} \quad \ldots (16)$$

where, A_2 denotes the false negative, true positive as M_2, true negative as A_1, M_1 denotes the false positive.

b) Sensitivity

The ratio of the correctly predicted stress level by the GOOBO-DSNN to an overall positive sample is termed sensitivity and is described as,

$$Sensitivity = \frac{M_2}{M_2 + A_2} \quad \ldots (17)$$

c) Specificity

The capability of GOOBO-DSNN in exactly predicting the true negatives is called its specificity and it is represented as,

$$Specificity = \frac{A_1}{A_1 + M_1} \quad \ldots (18)$$

d) Precision

The Precision is the positive predictions ratio that is true to all positive predictions and it is described as,

$$precision = \frac{M_2}{M_2 + M_1} \quad \ldots (19)$$

Comparative Investigation1 based on Learning Set

The comparative examination of the implemented GOOBO-DSNN for student stress level prediction technique using learning set is showed in Fig. 3. The accuracy-based estimation of the devised GOOBO-DSNN is depicted Fig. 3(a). For learning set of 90 %, the attained accuracy for the existing approaches RF, CALM-Net, GA + MLP, Ensemble model and proposed GOOBO-DSNN is 82.178%, 84.978%,

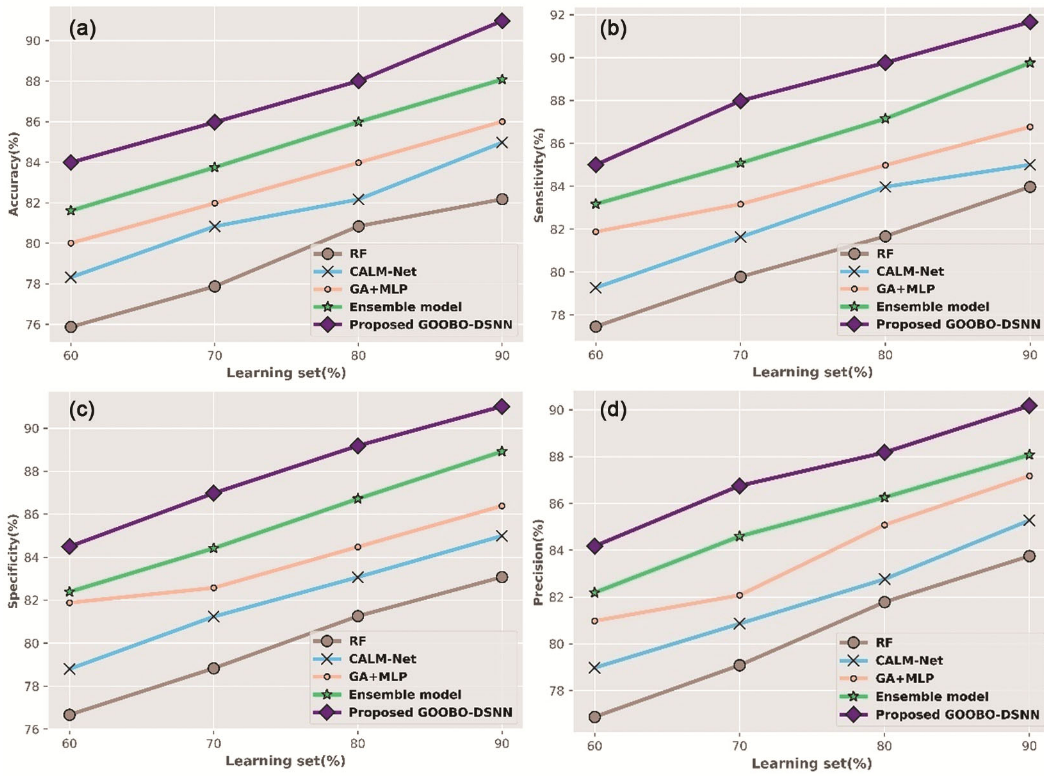

Fig. 3 — Comparative investigation (a) accuracy, (b) sensitivity, (c) specificity and (d) precision of the implemented GOOBO-DSNN based on the learning set

86.008%, 88.083% and 90.976% respectively. The examination of GOOBO-DSNN depending on the sensitivity is shown in Fig. 3(b). The sensitivity of the classical approaches like RF, CALM-Net, GA + MLP, Ensemble model and proposed GOOBO-DSNN are 83.978%, 85.009%, 86.777%, 89.754% and 91.664% correspondingly, with a learning set of 90%. The analysis of GOOBO-DSNN by specificity is presented in Fig. 3(c). If the learning set is 90%, the specificity of RF is 83.078%, CALM-Net is 84.994%, GA + MLP is 86.393%, the Ensemble model is 88.919 % and the proposed GOOBO-DSNN is 91.020%. In Fig. 3(d), the analysis of GOOBO-DSNN with precision is explained. When the learning set is 90% the precision attained for the traditional approaches i.e. RF, CALM-Net, GA + MLP, Ensemble model and proposed GOOBO-DSNN are 83.756%, 85.279%, 87.178%, 88.079% and 90.179% accordingly (Table 1).

Comparative Investigation 2 based on Learning Set

Different algorithms are taken for the evaluation of the proposed GOOBO + DSNN and they are SGD + DSNN, GA + DSNN and OOBO + DSNN. The algorithmic valuation of developed GOOBO + DSNN regarding performance metrics is displayed in Fig. 4. The assessment based on accuracy of the GOOBO + DSNN is presented in Fig. 4(a). The accuracy achieved by the developed GOOBO + DSNN for solution size 100 is 90.974%, while accuracy attained by other classical approaches like SGD + DSNN, GA + DSNN, OOBO + DSNN, are 85.898%, 87.235%, and 89.078%, respectively. The examination on the basis of the sensitivity of GOOBO + DSNN is displayed in Fig. 4(b). When the solution size is 100, the sensitivity attained by the traditional SGD + DSNN, GA + DSNN, OOBO + DSNN approach and the proposed GOOBO + DSNN approach are 86.987%, 88.008%, 89.768% and 91.698% accordingly. The examination of GOOBO + DSNN using specificity is displayed in Fig. 4(c). The specificity attained by SGD + DSNN is 86.443%, GA + DSNN is 87.622%, OOBO + DSNN is 89.423% and the proposed GOOBO + DSNN attained specificity of 91.336% for solution size 100. The GOOBO + DSNN attained the higher specificity of 2.09% and 5.35% than the OOBO + DSNN method and SGD + DSNN method respectively. The evaluation on the basis of precision is depicted in Fig. 4(d). The precision achieved by the proposed

Table 1 — Comparative Analysis 1

Metrics	learning Set	RF	CALM-NET	GA+MLP	Ensemble	Proposed
Precision	60%	76.879	78.979	80.979	82.188	84.179
Precision	70%	79.086	80.860	82.079	84.595	86.758
Precision	80%	81.786	82.766	85.085	86.259	88.179
Precision	90%	83.756	85.279	87.178	88.079	90.179
Specificity	60%	76.672	78.810	81.883	82.392	84.498
Specificity	70%	78.830	81.234	82.576	84.417	86.981
Specificity	80%	81.259	83.073	84.483	86.718	89.187
Specificity	90%	83.078	84.994	86.393	88.919	91.020
Sensitivity	60%	77.467	79.276	81.883	83.173	85.008
Sensitivity	70%	79.784	81.635	83.173	85.087	87.987
Sensitivity	80%	81.673	83.978	84.988	87.156	89.765
Sensitivity	90%	83.978	85.009	86.777	89.754	91.664
Accuracy	60%	75.876	78.323	80.008	81.610	83.988
Accuracy	70%	77.876	80.834	81.978	83.746	85.974
Accuracy	80%	80.844	82.167	83.979	85.987	88.008
Accuracy	90%	82.178	84.978	86.008	88.083	90.976

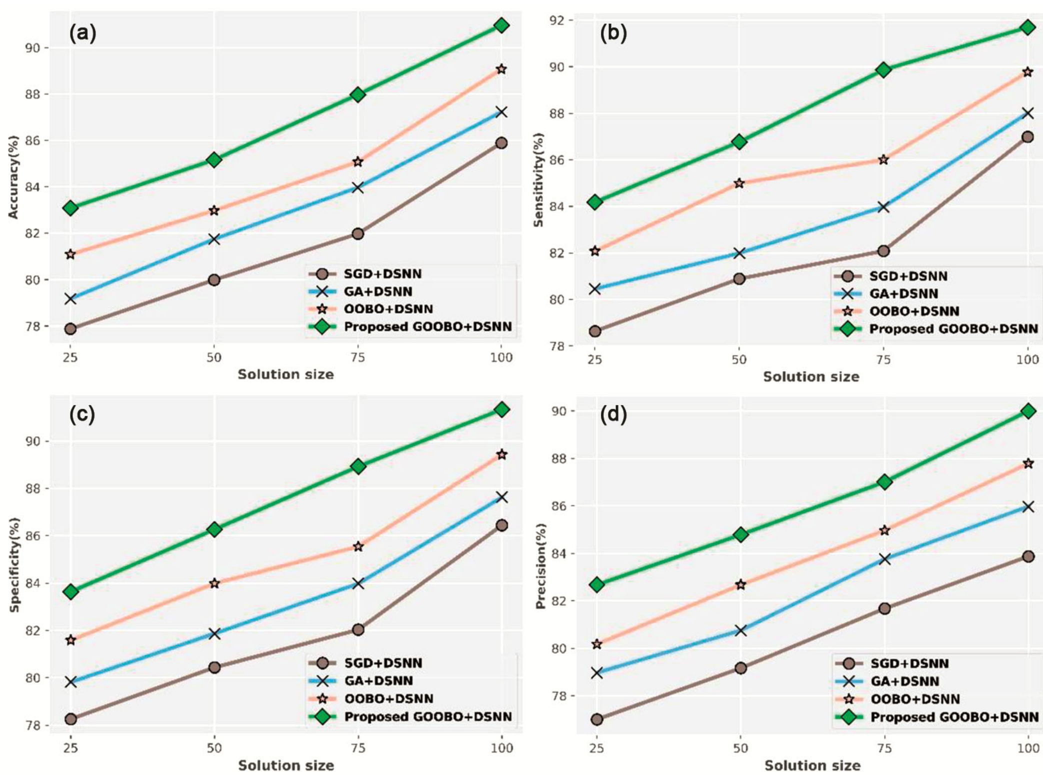

Fig. 4 — An Algorithmic Estimation of Devised GOOBO + DSNN Algorithm (a) Accuracy, (b) Sensitivity, (c) Specificity and (d) Precision

GOOBO + DSNN for solution size 100 is 90.001% and the traditional approaches, such as SGD + DSNN, GA + DSNN and OOBO + DSNN recorded precision of 83.876%, 85.976%, and 87.785% accordingly (refer to Table 2), here, the developed GOOBO + DSNN achieved precision by 2.46% and 4.47% higher than the OOBO + DSNN and GA + DSNN respectively.

Comparative Description

The comparative analysis of the proposed GOOBO-DSNN is portrayed in the Table 1. The

Table 2 — Comparative Analysis 2

Metrics	learning Set	SGD + DSNN	GA + DSNN	OOBO + DSNN	Proposed
Precision	25%	77.009	78.975	80.177	82.675
Precision	50%	79.168	80.755	82.675	84.787
Precision	75%	81.675	83.760	84.968	87.009
Precision	100%	83.876	85.976	87.785	90.001
Specificity	25%	78.256	79.816	81.582	83.634
Specificity	50%	80.437	81.868	83.983	86.267
Specificity	75%	82.031	83.977	85.543	88.923
Specificity	100%	86.443	87.622	89.423	91.336
Sensitivity	25%	78.638	80.454	82.076	84.179
Sensitivity	50%	80.887	81.987	84.987	86.767
Sensitivity	75%	82.084	83.978	86.008	89.867
Sensitivity	100%	86.987	88.008	89.768	91.698
Accuracy	25%	77.875	79.179	81.089	83.090
Accuracy	50%	79.987	81.749	82.978	85.167
Accuracy	75%	81.978	83.976	85.078	87.979
Accuracy	100%	85.898	87.235	89.078	90.974

proposed GOOBO-DSNN has achieved maximum precision, specificity, sensitivity and accuracy 90.179%, 91.020%, 91.664% and 90.976% when considering learning set of 90%. Likewise, the other techniques like RF, CALM-Net, GA + MLP and Ensemble mode achieved precision of 83.756%, 85.279%, 87.178% and 88.079% respectively. Similarly, the specificity achieved by the RF is 83.078%, CALM-Net is 84.994%, GA + MLP is 86.393%, and the Ensemble model is 88.919%. Moreover, the sensitivity attained by the traditional approaches such as RF, CALM-Net, GA + MLP and Ensemble mode is 83.978%, 85.009%, 86.777%, 89.754% and Also, the accuracy attained by the traditional approaches are RF, CALM-Net, GA + MLP and Ensemble mode are 82.178%, 84.978%, 86.008% and 88.083% (Values shown to three decimal points). The structural optimization of the DSNN with the proposed GOOBO enhances the method's efficiency in students stress level prediction as it improved the convergence rate and was successful in attaining global optima.

Conclusions

In this research, an optimization-based deep learning model GOOBO-DSNN is developed for the prediction of student stress levels. Here, the input data is taken from the database, and is allowed for data normalization by employing the log scaling method, and the normalized data is allowed for feature selection using Lorentzian similarity. Finally, the selected features are subjected to student stress level prediction using DSNN and the weights of DSNN are fine-tuned using the developed GOOBO algorithmic approach. Here, the GOOBO is designed by incorporating SGD and OOBO. Utilizing Deep Spiking Neural Network and SGD in our proposed model, it added to the enhancing effectiveness and attaining high accuracy of proposed model. SGD also helped the model with high accuracy in weights and facilitated to find the value of the optimal weight. The proposed GOOBO-DSNN attained the maximum accuracy, sensitivity, specificity, and precision, as compared to recent State-of-The-Art techniques. Currently this model is tested on single dataset only, this is the current limitation. In the future, hybrid of deep learning techniques may be considered to improve the efficiency of the method, moreover proposed model may be tested for other similar datasets also.

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