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An Efficient Deep Learning Model using Harris-Hawk Optimizer for Prognostication of Mental Health Disorders

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Abstract: Mental health disorders are primarily life style driven disorders, which are mostly unidentifiable by clinical or direct observations, but act as a silent killer for the impacted individuals. Using machine learning (ML), the prediction of mental ailments has taken significant interest in medical informatics community especially when clinical indicators are not there. But, majority studies now focus on usual machine learning methods used to predict mental disorders with few organized health data, this may give wrong signals. To overcome the drawbacks of the conventional ML prediction models, this work presents Deep Learning (DL) trained prediction model for automated feature extraction to realistically predict mental health disorders from the online textual posts of individuals indicating suicidal and depressive contents. The proposed model encompasses three phases named pre-processing, feature extraction and optimal prediction phase. The developed model utilizes a novel Sparse Auto-Encoder based Optimal Bi-LSTM (SAE-O-Bi-LSTM) model, which integrates Bi-LSTM and Adaptive Harris-Hawk Optimizer (AHHO) for extracting the most relevant mental illness indicating features from the textual content in the dataset. The dataset utilized for training consist of 232074 unique posts from the "SuicideWatch" and "Depression" subreddits of the Reddit platform during December 2009 to Jan 2021 downloaded from Kaggle. In-depth comparative analysis of the testing results is conducted using accuracy, precisions, F1 score, specificity, and Recall and ROC curve. The results depict considerable improvement for our developed approach with an accuracy of 98.8% and precision of 98.7% respectively, which supports the efficacy of our proposed model.

Keywords: Mental Health, Emotion, Adolescence, Sparse Autoencoder, Adaptive Harris Hawk Optimizer.

1. Introduction

Mental health, now been at the center of focus throughout all strata of population. The stressful lifestyle of the present age is leading to several psychological and behavioral issues [1]. The fast, competitive and a chase for a perfect life has generated tremendous mental pressures on all of us in different degrees, be it children or adults. Childhood-onset disorder brings more difficulty of negative results that persists in adults and adolescence. This disorder has challenges like unemployment, increase in suicide attempts and educational issues [2]. The disorder may also impact physical health of individuals if not treated at right time, and therefore mental disorder should be overcome by early measures. Psychopathological characteristics in childhood show the high risk for the onset of logical mental health disorders in adolescence. Identification of mental health disorders in adolescence is becoming a complex process, and it is affected by environmental, psychological, and biological factors [3].

Internal and external symptoms in childhood are generally accompanied by a high risk of mental disorders. Particularly, the impulsive behaviour is accompanied by the susceptibility of developing suicide and mental disorders [4]. Furthermore, neurodevelopmental diseases like Autism require frequent visits to the psychiatric and it is a life-long disorder. The complexities in learning also show mental health depression, which is generally found in children with neurodevelopmental diseases [5–8]. Some kinds of mental illness are personality issues, anxiety, bi-polar mood issues and depression [9]. Hence, it is concluded that this disorder affects day-to day activities, behaviors, emotions, and connectivity with society [10]. Even at the time of COVID-19 pandemic there has been an increase in the mental health issues because of the heavy usage of due to online education leading to more detrimental effects of EMF radiation [11].

In recent times, the advancement in medical and scientific applications have generated different clinical treatments and technologies for predicting this illness at the initial stages. In the world, it is estimated that approximately 460 million people are affected by mental illness [12-14]. Further, this illness is one of the major issues and general public health issues. For instance, depression is the major problem of disability and increases the risk of suicide attempts [15]. The early diagnosis of mental health issues is important for better understanding of mental illness and providing better protection to the [16–17]. The identification of chronic diseases is based on lab tests and analysis, but the mental health problems rely on the self-report of patients [18], which is quite late generally. However, due to advancements in information technology, tracking online contents and activity of individuals can lead to clues regarding onset of mental health disorders in individuals. In case of medical diagnosis, the process has to pass through various stages of uncertainty since the data which is obtained is mostly presented in linguistic format [19]. But, generally, finding the emotional indicators in text-sequences is a complex task because of long range dependencies involved in the text. The AI driven machine learning models help in knowledge extraction and enhance the prediction performance; further, this AI model can supplement the role of psychiatrists. These models play a major role in identifying the data obtained from the tools and help in prediction of mental health [20].

In the recent years the integration of information technology in health sector has ignited a prospective revolution in the area of health care [21]. The aim of the ML model is to develop computational models that can obtain hidden patterns automatically from the data. But the conventional ML models need a significant number of feature engineering models for better performance. However, this process is labor-intensive and time consuming. In recent times, the DL models are utilized in analyzing the healthcare data and providing better efficiency in treatment and diagnosis. The DL models are the end-to-end models that assist mapping the input features directly to the output via the multiple layered networks. Further, this network captures the hidden patterns present in the data. Moreover, optimizing the weights of the network enhances the prediction performance of the model. Motivated by this DL model, the present work utilizes a hybrid optimization assisted DL model for the prediction of mental health illnesses. DL plays a major role in the understanding of emotional indicators of textual content by handling dependencies and unstructured characteristics of the online data and can help in detecting mental health disorders quite early. The major aim of the proposed work is to develop a predictive model using Deep Learning training to assess the mental health disorders using textual contents.

The foremost contributions of our conducted research work are:

- To develop an automated optimal DL model for the mental health disorder using textual content of social media platforms.
- To carry out the feature extraction and prediction using the Sparse Auto-Encoder based optimal Bi-LSTM (SAE-O-Bi-LSTM) model.
- To optimize the hyper parameters of Bi-LSTM using the adaptive Harris-Hawk optimizer (HHO).

The rest part of the paper is organized in following sections: Section 2 throws light on the state of the art on the present literary works on prediction of mental health problems using varied AI techniques; Section 3 presents our proposed model for mental health problem prediction with the mathematical representation of the model and Harris-Hawk optimizer details; Section 4 analyzes the results and section 5 presents the strength and limitations and Section 6 presents the conclusions generated from our conducted research work and future work.

2. Literature Review

A literature review is a critical summary and evaluation of existing knowledge on a specific topic. The primary purpose of a literature review is to provide an overview of the current state of research on a particular topic. It helps to establish the context for a research study, identify gaps in knowledge, and justify the significance of the new research. Table 1 depicts the comprehensive LR stating the findings and research gap of the LR.

Table 1. Literature Review

Paper Title	Published Year	Author and Name of Conference/Journal	Findings
"Predicting mental health problems in adolescence using machine learning techniques" [22].	2020	"Tate, A.E., McCabe, R.C., Larsson, H., Lundström, S., Lichtenstein, P. and Kuja-Halkola, R. *PloS one"*	Developed a model for predicting the mental health problems for the generation belonging to the age group of mid adolescence

"Single classifier vs. ensemble machine learning approaches for mental health prediction" [23].	2023	"Chung, J. and Teo, J. *Brain Informatics"*	Presented a single classification as well the ensemble models for the prediction of mental health.
"Predicting mental conditions based on "history of present illness" in psychiatric notes with deep neural networks" [24].	2017	"Tran, T. and Kavuluru, R. *Journal of biomedical informatics"*	Predicted the psychiatric state on the basis of history of present illness. The attention based RNN (recurrent neural network) was used for the illness prediction
"Prediction of Mental Health Problem Using Annual Student Health Survey: Machine Learning Approach" [25].	2023	"Baba, A. and Bunji, K. *JMIR Mental Health"*	Worked on to develop model using ML for the mental health illness prediction based on the survey of annual student's health
"Negative emotions detection on online mental-health related patient's texts using the deep learning with MHA-BCNN model" [26].	2021	"Dheeraj, K. and Ramakrishnudu, T. *Expert Systems with Applications"*	Developed the multi-head attention based bi-directional convolutional network (MHA_BCN) for the detection of negative emotions on mental health issues.
"Prediction of mental health problems among higher education student using machine learning" [27].	2020	"Shafiee, N.S.M. and Mutalib, S. *International Journal of Education and Management Engineering (IJEME)"*	Reviewed the issues of mental health and related ailments for the students belonging to the higher secondary school age groups.
"Mental health prediction models using machine learning in higher education institution" [28].	2021	"Mutalib, S. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)"*	Developed model for higher education students using the ML models. Authors showed that the factors like anxiety, depression and stress were major for predicting the disorders.
"Identification of autism spectrum disorder using deep learning and the ABIDE dataset" [29].	2018	"Heinsfeld, A.S., Franco, A.R., Craddock, R.C., Buchweitz, A. and Meneguzzi, F. *NeuroImage: Clinical"*	Developed the DL model for autism disorder identification.
"An optimized deep learning approach for suicide detection through Arabic tweets" [30].	2022	"Baghdadi, Nadiah A., AmerMalki, HossamMagdyBalaha, YousryAbdulAzeem, Mahmoud Badawy, and MostafaElhosseini *PeerJ Computer Science"*	Developed optimization-based DL model to detect suicide from Arabic tweets.
"Prediction of mental health in medical workers during COVID-19 based on machine learning" [31].	2021	"Wang, Xiaofeng, Hu Li, Chuanyong Sun, Xiumin Zhang, Tan Wang, Chenyu Dong, and DongyangGuo. *Frontiers in public health"*	Predicted the mental health in clinical worker on COVID-19 pandemic. Here, the parameters were collected from 5108 clinical workers and 32 factors were gathered via questionnaire.

"Deep Learning for Cross-Diagnostic Prediction of Mental Disorder Diagnosis and Prognosis Using Danish Nationwide Register and Genetic Data" [32]	2022	Rosa Lundbye Allesøe et al. *JAMA psychiatry*	The prediction of mental health disorder and severity trajectories by investigating both a cross-diagnostic and single order setup. Results suggest that combining genetics and registry data to predict mental disorder and progression of disorder in
"An AI-based Decision Support System for Predicting Mental Health Disorders" [33]	2022	S. Tutun et al. *Information Systems Frontiers*	An intelligent decision support system (DSS) is proposed in this study with a sophisticated analytics and artificial intelligence that can accurately discover as well as diagnose various mental diseases. The given assessment tool was created using the Network Pattern Recognition (NEPAR) algorithm in the formation of DSSQUIZ. These responses, along with other historical data are then used to trained multiple machine learning models for detecting Participants' mental disorder if any and predict type of it (if present)
"Identifying suicide attempts, ideation, and non-ideation in major depressive disorder from structural MRI data using deep learning" [34].	2023	"Jinlong Hu et al *Asian Journal of Psychiatry, Elsevier"*	Developed deep neural network model to classify patients in three different categories named: SA (suicidal attempts)-vs-SI (suicidal ideation), SA-vs-NS (behaviors without suicidal attempts and ideation) and SI-vs-NS, respectively.
"A Review of Machine Learning and Deep Learning Approaches on Mental Health Diagnosis" [35].	2023	"Ngumimi Karen Iyortsuun, Soo-Hyung Kim, Min Jhon, Hyung-Jeong Yang, Sudarshan Pant *Healthcare, MDPI"*	Used online reviews and applied PRISMA review methodology to successfully diagnosed 33 articles suffering from schizophrenia, anxiety, depression, and related disorders.
"Depression and Suicide Risk Detection on Social Media using fastText Embedding and XGBoost Classifier" [36].	2023	"Sayani Ghosh, Amita Jain *International Conference on Machine Learning and Data Engineering, Elsevier"*	Developed a framework to discriminate patients suffering from depression and suicidal risks. The authors utilized fastText embedding for contextual analysis and TF-IDF vector for relevance of terms
"Harris hawks optimization: Algorithm and applications" [37]	2019	A. A. Heidari et al. *Future Generation Computer Systems*	The study simulate these patterns and behaviors mathematically in this work to construct an optimization function. We test the performance of this proposed HHO optimizer against standard nature-inspired strategies on 29 benchmark issues and some real-world engineering scenarios. The

			statistical results and comparisons indicate that the HHO algorithm is superior to several established meta-heuristic algorithms in most of instances.
"An adaptive Harris hawks optimization technique for two dimensional grey gradient based multilevel image thresholding" [38]	2020	A. Wunnava, M. K. Naik, R. Panda, B. Jena, and A. Abraham *Applied Soft Computing*	All 500 pictures from the Berkeley Segmentation Dataset (BSDS 500) were used to attain results proposed a multilevel thresholding of AHHO-based using I2DGG technique. It can be seen that they give better results compared to the recomended I2DGG method for 2D Tsallis Entropy and also against all the existing single level & multilevel OTMR techniques w.r.t. each base of entropy under consideration within these comparisons. Furthermore, the experimental results will be compared to other optimization-based multilevel threshold methods that reached state-of-the-art performance and they can show our proposal wt general purpose applicable in image segmentation.
"Advances in Manta Ray Foraging Optimization: A Comprehensive Survey" [39].	2024	"Farhad Soleimanian Gharehchopogh, Shafi Ghafouri, Mohammad Namazi and Bahman Aratesh *Journal of Bionic Engineering"*	The MRFO, which was introduced in 2020, is a revolutionary metaheuristic algorithm inspired by the unusual foraging behaviours of manta rays, notably cyclone, chain, and somersault. These biologically inspired systems provide excellent answers to complex physical constraints.
"An improved African vulture's optimization algorithm using different fitness functions for multi-level thresholding image segmentation" [40].	2024	"Farhad Soleimanian Gharehchopogh & Turgay Ibrikci *Multimedia Tools and Applications"*	Metaheuristic optimisation algorithms are used to address a variety of issues because they can solve problems with several dimensions in a reasonable amount of time and with high-quality outcomes.
"A multi-objective mutation-based dynamic Harris Hawks optimization for botnet detection in IoT" [41].	2023	"Farhad Soleimanian Gharehchopogh, Benyamin Abdollahzadeh, Saeid Barshandeh, Bahman Aratesh *Internet of Things, Elsevier"*	The importance of security implementation in digital platforms and the necessity to create defensive systems to identify diverse breaches prompted the researchers to examine updated and effective

			approaches, such as Botnet Detection for IoT systems
"Farmland Fertility Algorithm for Solving Engineering Optimization Problems" [42].	2023	"Farhad Soleimanian Gharehchopogh, Mohammad H. Nadimi-Shahraki, Saeid Barshandeh, Benyamin Abdollahzadeh & Hoda Zamani *Journal of Bionic Engineerin"*	Twelve chaotic maps have been integrated in FFA to determine the optimal number of prospectors to maximise the exploitation of the most promising solutions. Furthermore, the Quasi-Oppositional-Based Learning (QOBL) mechanism improves the exploration speed and convergence rate; dubbed the CQFFA method.
"Deep learning approach for brain tumour classification using metaheuristic optimization with gene expression data" [43].	2023	"Joshi et. al , *International Journal of Imaging Systems and Technology"*	The conducted study uses metaheuristic optimization techniques to improve model performance with gene expression data and focuses on brain tumor classification, with an emphasis on feature selection and model tuning.
"Gene selection with Game Shapley Harris hawks optimizer for cancer classification" [44].	2023	"Afreen, Sana, *Chemometrics and Intelligent Laboratory Systems"*	The authors have emphasized the importance of feature selection in improving classification accuracy and has used three classifiers, namely support vector machines (SVM), Naive Bayes (NB), and K-nearest neighbors (KNN), to assess the selected genes efficacy and their impact on classification accuracy.
"Applications and techniques of machine learning in cancer classification: A systematic review" [45].	2023	"Yaqoob, Abrar, Rabia Musheer Aziz, and Navneet Kumar verma, *Human-Centric Intelligent Systems"*	The authors have reviewed various machine learning techniques applied to cancer classification and focuses on the systematic review of different methodologies, including supervised and unsupervised learning approaches.

The state of the art in mental health disorder prediction has extensively utilized conventional ML models, however it is evident that empirical evaluations and assessment of deep learning models is not explored in this context.

2.1 Research Gap

Following are the research gap identified by the extensive LR.

- Deep Learning Models have not been explored.
- Use of Activation Function is not explored.
- Specific disease has not been taken care of.

3. Proposed Methodology

Mental health prediction in adolescence is one of the important segments to reduce the possibilities of mental issues. The conventional statistical approaches are complex to identify the influence of random interference criteria on mental health. Further, the ML models utilized for mental health prediction focused only on the prediction accuracy and don't consider the influence of feature parameters. To tackle these challenges, this work aims to predict mental health in adolescence using optimization-based DL model. This model extracts and predicts the most import features which are essential for mental health prediction from the textual contents of the users. Figure 1 shows our proposed modular diagrammatic representation of mental health prediction in adolescence using Deep Learning.

3.1 Dataset acquisition

The dataset utilized for predicting the mental health in adolescence is obtained from the Kaggle open data set repository through URL https://www.kaggle.com/datasets/nikhileswarkomati/suicide-watch. This dataset is set of 232074 unique posts from the depression and suicide watch of the Reddit from 2008 December to January 2021.

3.2 Experimental Setup

Python has been used for experimental purpose. Python's popularity in deep learning stems from its straightforward syntax, readability, and rich libraries such as Tensor Flow and PyTorch, specifically designed for machine learning. Its clear structure speeds up development, minimizes mistakes, and improves accessibility for users of all levels. Python's active community provides strong support, encouraging continuous innovation and rapid progress in deep learning techniques and applications.

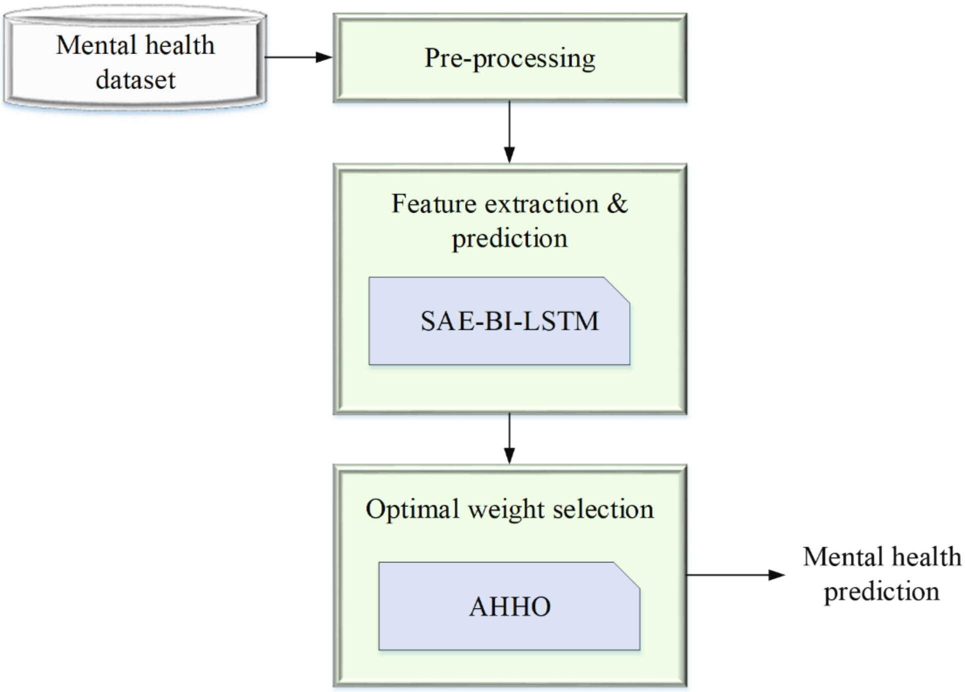

Figure 1. Diagrammatic representation of Deep Learning based mental health prediction

Together, these attributes establish Python as the preferred language among researchers, developers, and practitioners in the deep learning domain.

3.3 Pre-processing

Initially, the pre-processing stages like stop words removal, stemming, and lemmatization are carried out. Initially, the stop words removal process is carried out. Stop words like prepositions and articles don't have meaning and don't provide any advantages to mental health prediction. Stemming is the method of removing the ending of terms for identifying the root type. After the stemming process, lemmatization is carried out. Lemmatization is the method of merging different words and eliminating the word's dimensionality.

Missing data has been handled by using imputation where missing values have been replaced with a reasonable estimate. Outliers were detected and handled using box pots techniques. According to the outliers, the strategy of handling them is decided like whether to transform it or truncate or impute it. Duplicate records have also been discarded or removed from the database. Fuzzy matching is used to handle typos and spelling errors.

3.4 Notations

Table 2 is depicting the notations which has been used for mathematical equations. The working of proposed algorithm is explained mathematically in further sections.

Table 2. Notations used in mathematical equation

Notation	Meaning
$W^{(1)}$	Weighting Term
$I(W,b)$	Loss function
$K-L$	kullback-Leibler divergence
$\vec{h}_t$	Forward LSTM
Y_{rab}	position of prey (rabbit)
Y_{rand}	Random walk position

3.5 Optimal feature extraction and classification

SAE: After pre-processing the data, to predict the mental health disorder, the DL model SAE-O-Bi-LSTM is utilized for optimal feature extraction and classification. This DL model overcomes the hand-crafted feature extraction and conventional ML model classification. The DL model SAE is the extension model of AE (auto encoder). This SAE uses the sparse coding as well as sparse penalty ρ on the basis of AE. This deep network has input (IL), hidden (HL) and output layers (OL). In SAE, the hidden layer is able to learn the sparse feature representation from the input layer. Let the sample z obtained from the dataset $Z=\left[z_1, z_2, \ldots\ldots\ldots, z_n\right]$. In the hidden layer, the computation of activation function 'h' is done using equation (1):

$$h = g(W^{(1)}z + b^{(1)}) \tag{1}$$

where $W^{(1)}$ is the weighting term and it integrates the IL and HL, $b^{(1)}$ is the bias and g is the activation function. The weight of HL and OL is utilized for reconstructing the hidden data. The reconstructing data $\tilde{z}$ is computed using equation (2):

$$\tilde{z} = g(W^{(2)}z + b^{(2)}) \tag{2}$$

Where $W^{(2)}$ is the weighting term and it integrates HL and OL; $b^{(2)}$ is the bias.

During the training process of SAE, the $W^{(1)}$, $W^{(2)}$, $b^{(1)}$, and $b^{(2)}$ are randomly initialized. Once the parameters are initialized, the SAE carries out the forward propagation and computes the value of activation in the HL. Then, these computed activation values are utilized for reconstructing the original data in the OL. Finally, the SAE's loss function is given as equation (3):

$$I(W,b) = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{1}{2}\| z_j - \tilde{z} \|^2\right) + \frac{\beta}{2}\sum_{n=1}\sum_{j=1}\sum_{k=1}\left(W_{jk}^{(n)}\right) \tag{3}$$

Where $I(W,b)$ is the loss function, n is the layers in the network, β is the weight decay variable and $W_{jk}^{(n)}$ is the weighted term between the layers like n and $n+1$.

The mean activation function of k^{th} neurons in the HL is defined as shown in equation (4):

$$\rho_k = \frac{1}{m}\sum_{j=1}^{m} h_k(z_j) \tag{4}$$

Adding the ρ for limiting the activation function in the HL of the SAE. The computation of every node in the HL is given as equation (5):

$$K - L(\rho\rho_k) = \rho\log\frac{\rho}{\rho_k} + (1-\rho)\log\frac{1-\rho}{1-\rho_k} \tag{5}$$

Where $K-L$ is the kullback-Leibler divergence and ρ_k is the degree of activation. The loss function by adding the sparse limit is given as equation (6):

$$I_{sparse}(W,b) = \alpha \times K - L(\rho\rho_k) + I(W,b) \tag{6}$$

Where α is used for controlling the ρ.

The network SAE is utilized for extracting features from the input data to reduce the dimensionality of the textual data. Once, the dataset is pre-processed, the input feature vector of SAE is reduced to the size of $(48,1)$ with a total 48 neurons in the input layer as shown in Figure 2.

In this work, only one HL is utilized to improve the computation and minimize the reconstruction error. There are two scenarios considered for the activation function. In the initial scenario, for encoding and decoding, sigmoidal activation function is employed. In the next scenario, the sigmoidal function is employed in the encoding process whereas linear transfer function is employed in the decoding process. Figure 2 shows the results of SAE's training in various activation functions and various neurons. The reconstruction error considered in the initial scenario is higher than the second scenario, hence the second scenario is chosen. Further, the number of neurons utilized for the training process is 24.

O-Bi-LSTM: The LSTM network utilizes only the prior features for predicting the further information. But, the Bi-LSTM is able to learn the features in the forward as well backward direction. The horizontal direction computes the hidden vector $\vec{h}_t$ in forward LSTM and thevertical direction computes the hidden vector $\overleftarrow{h}_t$ in forward LSTM. Finally, the hidden states are connected for computing the final mental health prediction. These two hidden states are indicated as shown in equation (7) and (8) and utilized in equation (9):

$$\vec{h}_t = LSTM\left(y_t, \vec{h}_{t-1}\right) \tag{7}$$

$$\overleftarrow{h}_t = LSTM\left(y_t, \overleftarrow{h}_{t-1}\right) \tag{8}$$

$$z_t = W_{\vec{h}z}\vec{h}_t + W_{\overleftarrow{h}z}\overleftarrow{h}_t + b_z \tag{9}$$

Where $LSTM\,(\,)$ is the LSTM term, b_z is the term, y_t is the input to the network, $W_{\vec{h}z}$ and $W_{\overleftarrow{h}z}$ are the weighting terms of forward and backward LSTMs. Figure 3 defines the architecture of SAE-O-Bi-LSTM.

feature vector $(24,1)$ using the SAE is integrated into the prior feature vector $(12,1)$ of mental health features. This creates the augmentation prior feature vector $(36,1)$.

Finally, this $(36,1)$ Then, the augmentation is created on $(36,1)$ feature vector and passed to the Bi-LSTM model. In Bi-LSTM, the outcomes of forward and backward LSTMs are integrated to the one neuron with FC (fully connected) layer. The FC layer is utilized for predicting mental health and also enhances the generalization ability. In this Bi-LSTM network, the parameters like layers, batch size and units are optimized by the metaheuristic algorithm AHHO (adaptive Harris Hawk Optimizer) [35-36]. During the initialization process, every HH (Harris Hawks) is computed with the fitness value via fitness function shown in equation (10).

$$Fitness = Max\,(Accuracy) \tag{10}$$

The AHHO mimics the chasing and cooperative characteristics of HH (Harris Hawks) in nature. This optimizer is able to balance between the exploration and exploitation stages. The exploration stage portrays the model where the HH is unable to trace the preys. In this AHHO, the candidate's solutions are the HH and the best solution obtained is the prey. The HH settles randomly in various positions and looks for the prey with two parameters that are chosen on the basis of probability l .Here, when $p \geq 0.5$, the HH settles on the random trees and it has random positions over the range of population.

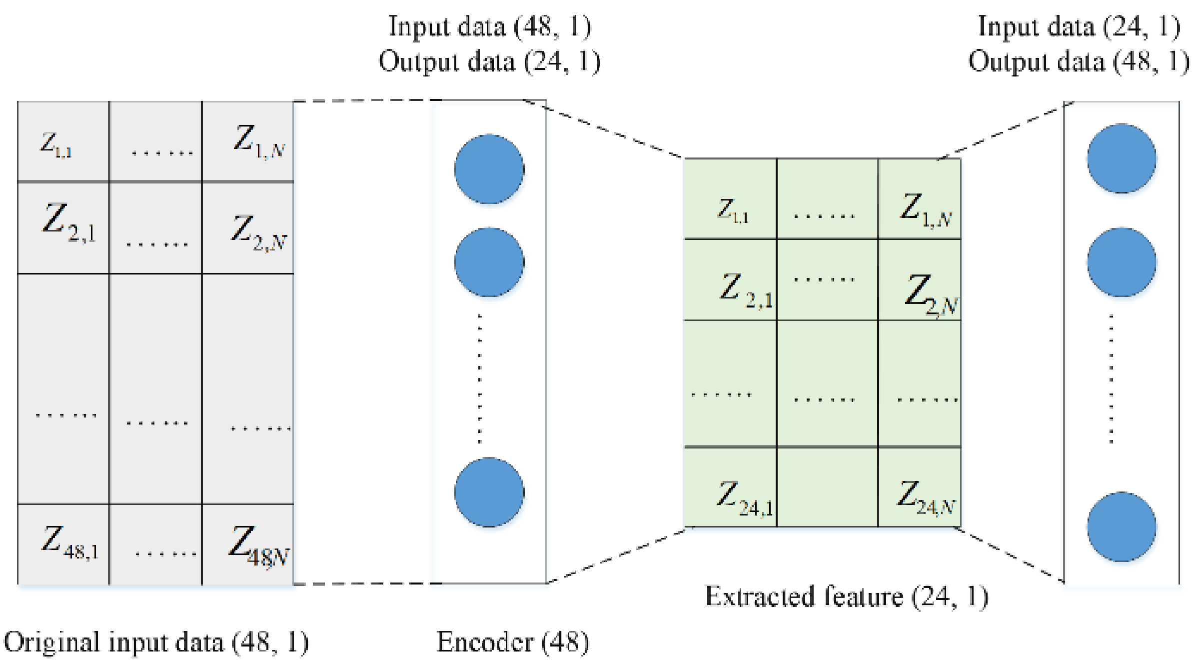

Figure 2. Structure of SAE

Initially, the input feature vector $(48,1)$ is given as input to SAE and the output of HL is extracted as the

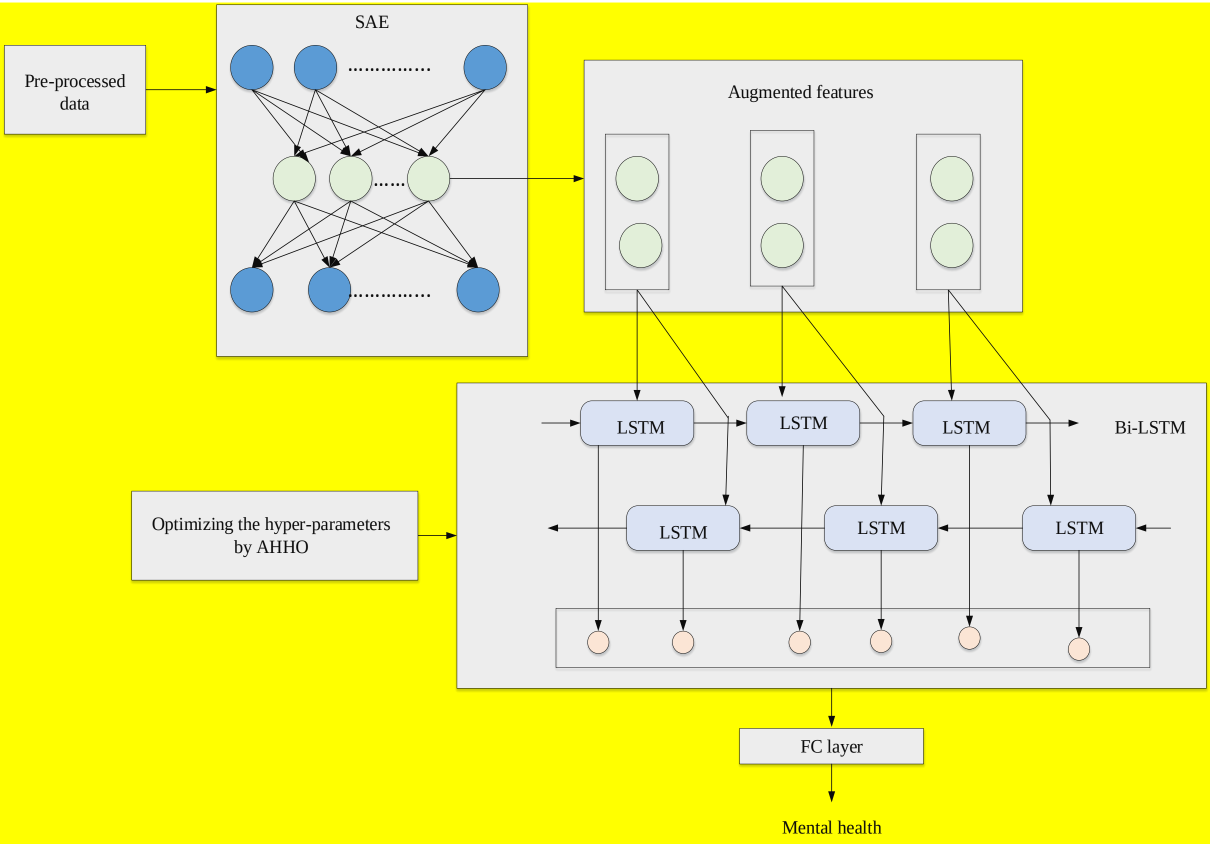

Figure 3. Architecture of SAE-O-Bi-LSTM

When $p < 0.5$, the HH settles by the other member's position and the rabbit as shown using equation (11).

$$Y(t+1) = \begin{cases} Y_{rand}(t) - r_1 \,|\, Y_{rand}(t) - 2r_2 Y(t) \,| & p \geq 0.5 \\ Y_{rab}(t) - Y_m(t) - r_3(LL + r_4(UL - LL)) & p < 0.5 \end{cases} \quad (11)$$

Where Y the position of search agents (Harris Hawks) is, Y_{rab} is the position of prey (rabbit), $Y_m(t)$ is the mean position of hawks, Y_{rand} is the random walk position, 'UL' and 'LL' are the upper and lower limits respectively. The symbols 'r_1, r_2, r_3' and 'r_4'; represent random numbers in the equation.

The transformation from exploitation to exploitation happens when it varies among different exploration characteristics on the basis of escaping energy levels of the prey. It is represented using equation (12):

$$E_e = 2E_0\left(1 - \frac{t}{T}\right) \quad (12)$$

Where 'E_e' and 'E_0' are the treated as escaping energy and initial energy respectively whereas 't' and 'T' represents iteration and maximum iteration.

If $r \geq 0.5$ and $|E_e| \geq 0.5$, then the prey has more energy and it tries to run away using misleading shifts. However, it is not able to escape from the place and it is expressed as equation (13) and (14):

$$Y(t+1) = \Delta Y(t) - E_e \,|\, JY_{rab}(t) - Y(t) \,| \quad (13)$$

$$\Delta Y(t) = Y_{rab}(t) - Y(t) \quad (14)$$

Where J is the jumping speed of rabbit, $\Delta Y(t)$ is the variation among position vectors for all preys and the current location.

In the hard encircle, when $r \geq 0.5$ and $|E_e| < 0.5$, the prey state becomes extremely tired having very less escaping energy. The HH then surrounds and attacks the prey, thereby the present location is updated by using equation (15):

$$Z = Y_{rab}(t) - E_e \,|\, \Delta Y(t) \,| \quad (15)$$

In the soft encircles, when $r \geq 0.5$ and $|E_e| \geq 0.5$, the prey attains more energy to escape and it applies a soft besiege before the attacking process. The term Levy's flight is developed for imitating the different motion dives of HH and prey. It is given by equation (16):

$$X = Z + V \times Levy\,(D) \quad (16)$$

V is the random vector and $Levy\,(D)$ is the Levy's flight function in above equation (16) . The last stage of this model is the position updation of HH and it is given as equation (17)

$$Y(t+1)=\begin{cases} Z & when\ Levy\,(Z) < Levy\,(Y(t) \\ X & when\ Levy\,(X) < Levy\,(Y(t) \end{cases} \tag{17}$$

When $r<0.5$ and $|E_e|\geq 0.5$, the AHHO defines the hard besiege using progressing rapid dives. In this stage, the prey doesn't have sufficient energy to escape and the HH attacks the prey. In this stage, the HH look for the minimization of distance among the prey and the mean position. Equation (7) defines this process and the values of X and Z are derived by the following equation (18):

$$Z=Y_{rab}(t)-E_e\,|\,JY_{rab}(t)-Y_m(t)\,| \tag{18}$$

In AHHO, the position of all the variables in search space is determined by Equations (1) to (8). At last, the initial search agent for the new position of standard HHO $Y_i(t)$ is given as $Y_{i-AHHO}(t+1)$. The following expression is introduced for attaining better convergence in accuracy performance and not trapped by local optima.

For this, the radius $Rad(n)$ as shown in equation (19) is obtained by including the Euclidean distance between the current locations of HH $Y_i(t)$ and the position of candidate solution Y_{i-HHO}.

$$Rad(n)=\|\,Y_i(t)-Y_{i-AHHO}(t+1)\,\| \tag{19}$$

In the position updating phase, the best HH is selected by fitness comparison of two HH $Y_{AHHO}(t+1)$ and $Y_{i-AHHO}(t+1)$ using equation (20).

$$Y_i(t+1)=\begin{cases} Y_{i-HHO}(t+1) & when\ f(Y_{i-HHO}) < f(Y_{i-AHHO}) \\ Y_{i-AHHO}(t+1) & elsewhere \end{cases} \tag{20}$$

Algorithm, as shown in Figure 4 below shows the pseudocode for weight updation using AHHO. The integration of SAE with O-Bi-LSTM enhances the training time and also increase the mental health prediction accuracy.

Algorithm: Pseudocode for weight updation using AHHO

Input: Set the HH, maximum iteration, layers, batch size and units
Output: Optimal parameters
Set all HHs locations
while (stopping criteria is met) **do**
  Compute the fitness of all HHs
  Set the prey's best position
for every Y_i **do**
  Estimate the exploration characteristics using equation (12)
  When energy is greater than 1, **then**
    Location vector is updated using equation (11)
  When energy is less than 1, **then**
    When $r\geq 0.5$ and $|E_e|<0.5$, **then**
      Location vector is updated using equation (14)
  When $r\geq 0.5$ and $|E_e|<0.5$
    Location vector is updated using Equation (15)
  When $r\geq 0.5$ and $|E_e|\geq 0.5$
    Location vector is updated using Equation (16)
  When $r<0.5$ and $|E_e|\geq 0.5$
  Update $Y_{i-AHHO}(t+1)$ position vector using Equation (17)
Then
Update $Y_{i-AHHO}(t+1)$ position vector using Equation (19)
end for
  Select the best $Y_{AHHO}(t+1)$ and $Y_{i-AHHO}(t+1)$
  Update the parameters
end for
end while
Return the best outcome

Figure 4. Pseudocode: Weight updation using AHHO

4. Results Analysis

The evaluation of the work is carried out in the Python. Following Table 3 shows the hyper-parameters setting utilized for conducting the experimentations.

The considered dataset is split into training, validation and testing sets with a division ratio of 70%, 20% and 10% respectively.

4.1 Performance Measures

For validating the performance, the measures like 'accuracy', 'recall', 'precision', 'F1-score' and 'specificity' are utilized.

Accuracy: It is one of the major measures utilized for classification quality assessment. It is the ratio between the numbers of accurate predictions to the overall predictions.

Recall: This metric is utilized for measuring the ratio of actual positives predicted out of all the positive cases.

Precision: This measure is utilized for checking the positive prediction of the model by calculating the ratio between correct positive predictions out of all the positive predictions.

F1-score: This measure is the harmonic mean of Precision and Recall.

Specificity*:* This measure shows the ability of model to accurately detect non-suicide features. It is utilized for measuring the ratio of actual negatives that are accurately identified out of all the negative identified cases.

4.2 Comparative Analysis

The following section presents the in-depth comparative analysis of the prediction results of approaches named LSTM, SAE, BiLSTM and our proposed approach SAE-O-BiLSTM. The performance measures like accuracy, recall, precision, F1-score, specificity, ROC (region of characteristics) and confusion matrix are presented. Figure 5 shows the comparison of performance measures like accuracy, recall and precision. In Figure 5 (a), the accuracy values achieved by the LSTM, SAE, BiLSTM and the proposed (SAE-O-BiLSTM) are 93.4%, 96.1%, 95% and 98.8% respectively. Figure 5 (b) depicts the recall values of the proposed and the existing approaches. It is observed that the recall values achieved by the proposed mental health prediction model are 23.12% better than LSTM, 12.7% better than BiLSTM and 8.7% better than SAE models. Similarly, in Figure 5 (c) also the proposed mental health prediction model achieved better precision value.

Figure 6 shows the comparison of performance measures like F1-score and specificity and it is compared with the approaches like LSTM, SAE, BiLSTM and the proposed SAE-O-BiLSTM. It is observed from both Figures that the F1-score and specificity values achieved by the proposed SAE-O-BiLSTM are 99.0% and 98.8% and better when compared to other approaches. It is also observed that the proposed SAE-O-BiLSTM not only attained better prediction outcomes but also it is a robust model. This improvement is due to the integration of SAE with BiLSTM and the AHHO. The AHHO algorithm selected the better optimal value and attained better performance.

Figure 7 depicts the performance of SAE-O-BiLSTM using accuracy and loss curve comparison. The performance comparisons are carried out by examining the variation of the epochs from 20 to 140. It is evident from Figure 7 (a) that training and testing accuracy is enhanced using epochs between 40-60. Further, it is also noted the accuracy is nearly stable after the 40th epoch for both training and testing accuracies. It is also observed in Figure 7 (b) that the training as well as testing losses are stable after the 40th epoch.

Table 3. Hyper-parameters

Hyper-parameters	**Values**
Size of batch	120
Epochs	140
Learning rate	0.001
Forward and backward hidden units	300
FC	1
Optimizer	AHHO

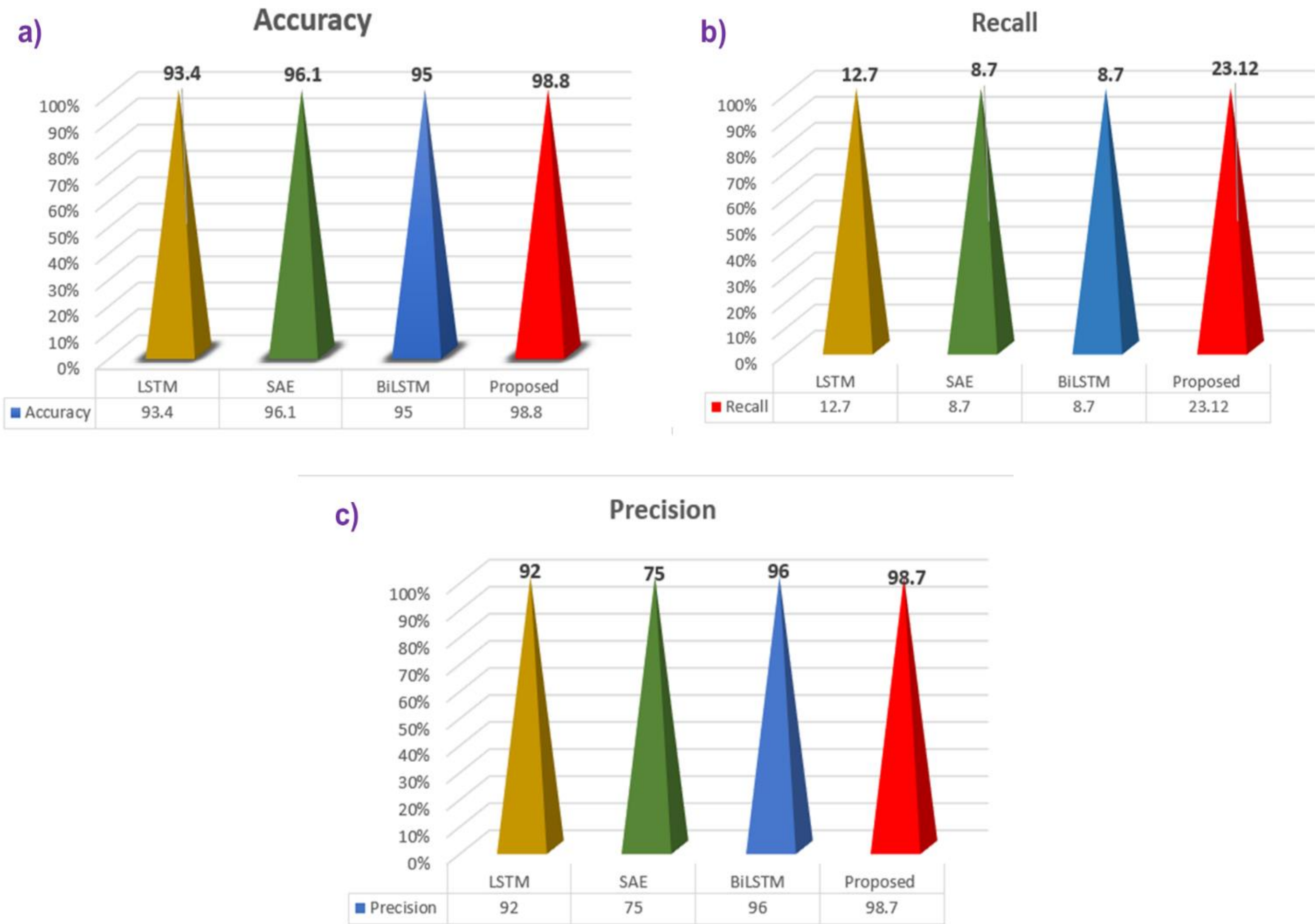

Figure 5. Comparison of (a) accuracy, (b) recall and (c) precision

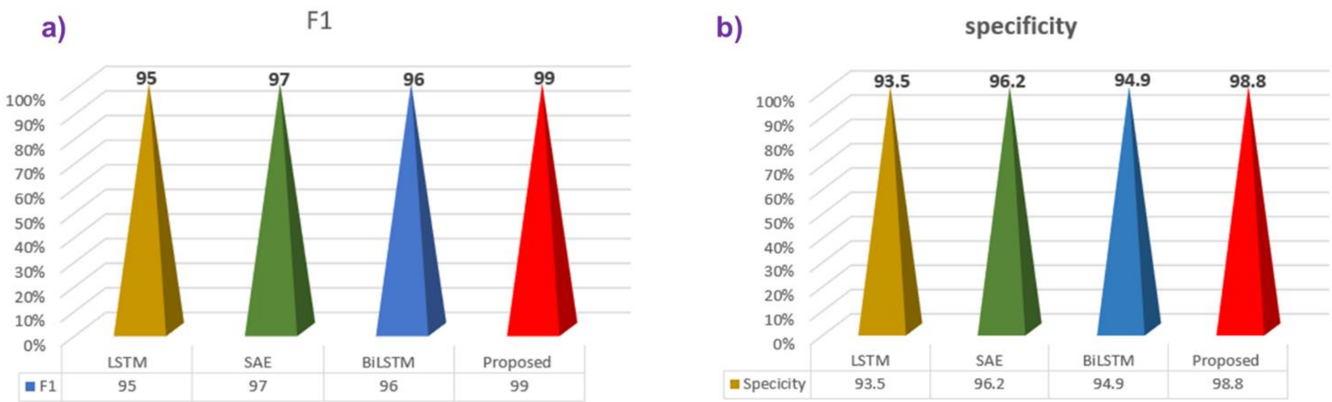

Figure 6. Comparison of (a) F1-score, (b) and specificity

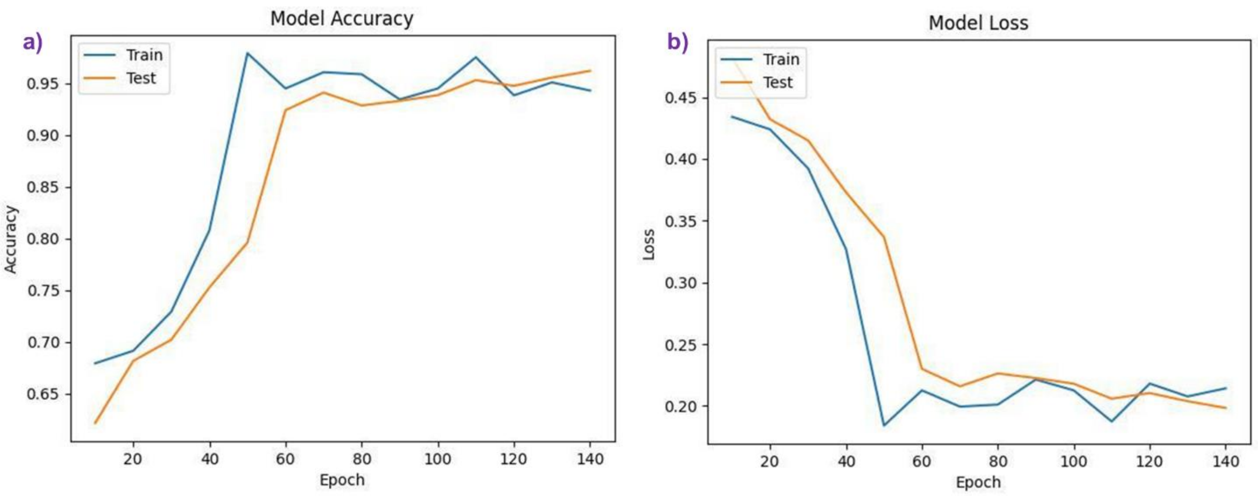

Figure 7. Performance of SAE-O-BiLSTM (a) accuracy curve and (b) loss curve

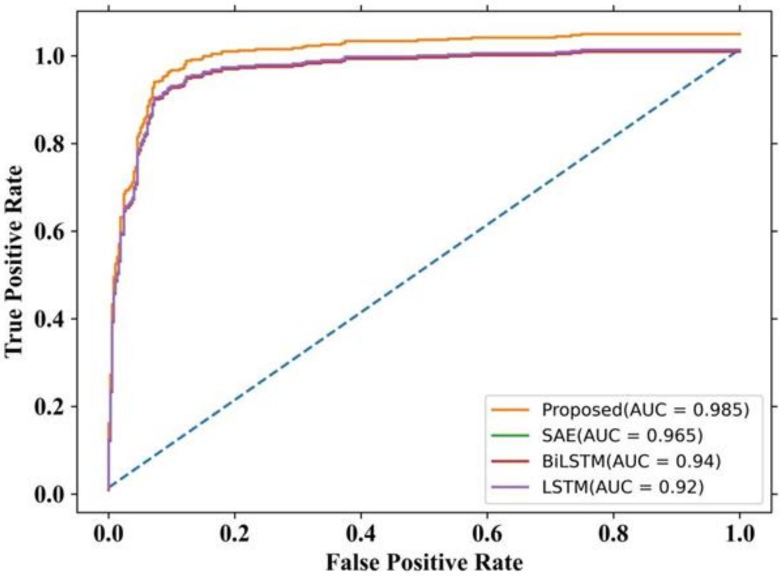

Figure 8. ROC performance of the various approaches

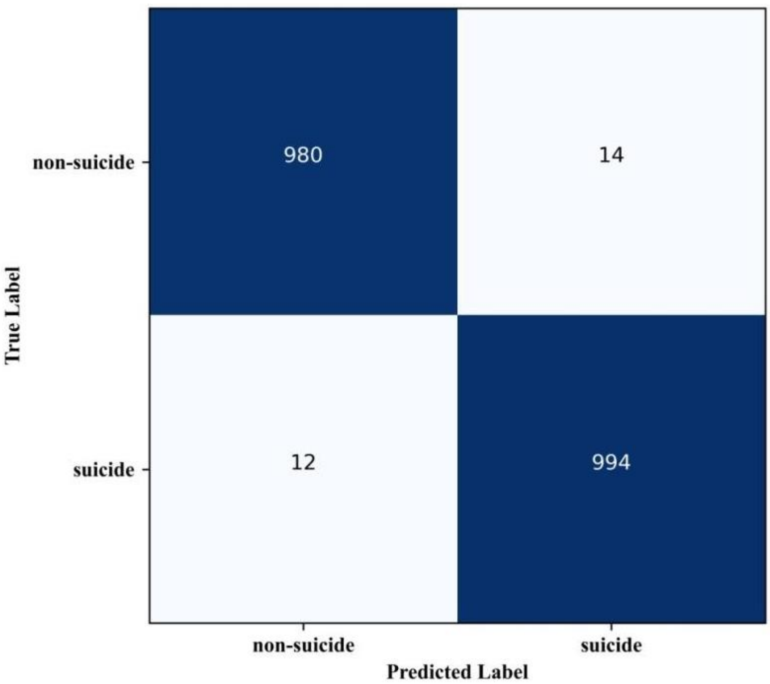

Figure 9. Confusion matrix of the proposed SAE with O-BiLSTM

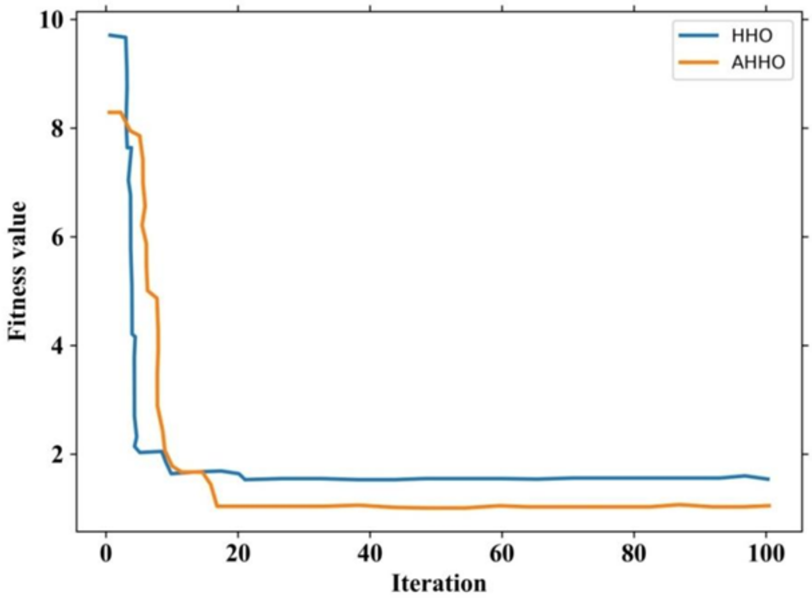

Figure 10. Convergence analysis of the AHHO and HHO

Table 4. Evaluation matrix

	Predictive Positive	Predictive Negative
Actual Positive	980 (TP)	14(FN)
Actual Negative	12(FP)	994(TN)

ROC curve is utilized for showing the performance of binary classification. 'AUC' (area under the curve) is used for visualizing the balance among 'FPR- False Positive Rate' and 'TPR-True Positive Rate' by considering the threshold value. Better classification model should have 'AUC' value of nearly 1. It is observed from the graph shown in Figure 8, that the 'AUC' value of the proposed model is 0.985 and the AUC values achieved by the LSTM, SAE-O-BiLSTM are 0.92, 0.965 and 0.94 respectively.

Figure 9 presents the generated confusion matrix of our proposed SAE-O-BiLSTM. The classes like 'suicide' and 'non-suicide' are predicted It is observed that there are 980 samples are predicted as non-suicide and 14 are misclassified. Similarly, it is observed that there are 994 samples are predicted as suicide and 12 are misclassified. Table 4 shows the evaluation metrics of the proposed data as per the confusion matrix.

In above table 4, TP stands for True Positive, FN stands for False Negatives, FP stands for False Positives and TN stands for True Negative. As per the confusion matrix results obtained TPR(True Positive Rate) can be calculated as the ratio of TP with respect to actual positives (TP + FN) in the datasets which comes out to be 0.98. FPR (False Positive Rate) can be calculated as the ratio of FP with respect to actual negatives (TN+FP) which comes out to be 0.01. False Negative Rate (FNR) and True Negative Rate (TNR) can be calculated by calculating the ratio of FN with respect to actual positives(TP+FN) and TN with respect to actual negatives(TN+FP) respectively. FNR and TNR of our classifier turns out to be 0.007 and 38.23. The values are indicative of efficacy of our trained classifier.

Figure 10 depicts the analysis of the convergence performance of the AHHO and HHO with respect to the fitness value. It is observed that when the value of iteration is 20, the fitness value is 1.4 for AHHO and 1.9 for the HHO. Similarly, for all iterations, the AHHO attained better performance when compared to the HHO. Hence, it is proved from the graph that AHHO doesn't affect by the local optima and has better convergence.

4.3 Discussion

Mental health experts utilize different assessment tools for detecting and diagnosing mental disorders. But, these tools are complicated, have more questionnaire analyses and need more time for completing the process. Moreover, the outcomes obtained from these models should be interpreted and manually analyzed by experts and attained incorrect predictions. To tackle these challenges optimization based automated DL models for mental health prediction in adolescence are developed. The model extracted the features automatically and then tuned the hyperparameters of the network by using the nature inspired optimization methodology of AHHO for performance enhancement. The experimental finding proves how the DL based model can efficiently identify and diagnose mental health. Moreover, the analysis significantly minimizes the cost and time required by the medical experts to make decisions.

5. Strength and Limitation of the study

This study presents several significant strengths, demonstrating the potential impact and innovation of our deep learning model using the Harris-Hawk Optimizer for the prognostication of mental health disorders. The study also presents the limitations which are given below.

- Small dataset and limited diversity in the dataset.
- Limited features are there in the existing dataset that can be further increased.
- While the Harris-Hawk Optimizer may be efficient, there might be other optimizers that could potentially offer better performance or faster convergence.

6. Conclusions and Future Directions

The robustness and efficiency of conventional machine learning based mental health prediction is less, due to varied factors such as non-availability of structured medical data, non-linearity of the dependent and independent variables of medically assessed variables and textual data feature extraction. Further, these models can't define the better features which are essential for prediction and mainly relied on the hand-crafted features. To tackle these challenges, this work presented in this paper presented a deep learning modular approach by utilizing Sparse Auto-Encoder based optimal BiLSTM model (SAE-O-BiLSTM) for mental health prediction in adolescence. The main novelty of the work is combining the SAE with BiLSTM while parallel updation of hyper-parameters by nature inspired AHHO algorithm. The experimental analysis proved that the proposed SAE with O-BiLSTM achieved better performance when compared to other approaches. Thus, it was proved the proposed SAE with O-BiLSTM will provide an efficient solution to mental health prediction in adolescence. This work will be extended by considering the huge data with large parameters for increasing diagnostic performance bias of the model. In addition to that more DL models will be considered and the performance will be analyzed. In the future, severity of the suicide attempt can be predicted using various machine learning models and Performance will be compared to other models that are considered state-of-the-art, and the best methods for mental health prediction will be found.

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Vandana: Conceptualization, methodology, Data collection, implementation, Writing - Original Draft, Writing - Review & Editing; **Shilpa Srivastava**: Conceptualization, Methodology, Visualization, Data Validation, Result Analysis, Writing - Review & Editing. **Nidhi Arora**: Formal Analysis, Conceptualization, Validation, Writing - Review & Editing; **Varuna Gupta**: Conceptualization, visualization, Writing - Review & Editing. All the authors read and approved the final version of the manuscript.

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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