SSO-FFNN: A Scalable Seeker Optimization-Enhanced Feedforward Neural Network for Predicting Anxiety Levels in College Students

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This study aims to predict anxiety among college students using optimization-enhanced neural network models instead of conventional machine learning. The student anxiety and depression dataset from Kaggle (6,982 records) was analyzed through comprehensive text preprocessing (tokenization, stop-word removal, TF-IDF feature extraction, and SMOTE balancing), exploratory data analysis, and a set of baseline models including ANN, RNN, ES-ANN + LOF, Harmony-Search ANN, and GA-BP ANN. To address the limitations of earlier approaches, a new SSO-FFNN (Scalable Seeker Optimization-Enhanced Feedforward Neural Network) framework was introduced, where the SSO algorithm optimizes network weights and biases to avoid local minima and improve convergence speed. Results show that the proposed SSO-FFNN achieved 97 % accuracy, an F1-score of 0.84, and a ROC-AUC of 0.97, outperforming all baseline models. These findings highlight the potential of optimization-driven neural networks for early anxiety detection and timely preventive counselling in academic settings.

Povzetek: Študija predstavlja izboljšan nevronski model za napovedovanje anksioznosti pri študentih, ki omogoča natančnejše zgodnje prepoznavanje težav.

1 Introduction

The forecasting and early identification of mental health diseases have gained prominence in recent years because to the worldwide increase in psychological ailments, especially among young adults and students. Progress in computational intelligence and machine learning has facilitated the creation of predictive models capable of detecting early signs of psychiatric disorders, including anxiety, depression, and stress. Neural networks have emerged as a powerful technology capable of representing complex non-linear relationships in data and delivering highly accurate predictions.[1]. In contrast to conventional statistical methods, neural networks can identify latent patterns in varied datasets, rendering them especially proficient for the study of text-derived psychological signals from student responses

The prevalence of mental health concerns among college students and young people has been an increasing concern globally. Academic pressure, social challenges, and uncertainty from global events such as the COVID-19 pandemic have intensified stress, anxiety, and depression among students [2]. Traditional assessments such as questionnaires and interviews often suffer from bias, underreporting, and limited scalability. Conversely, computational models utilising neural networks provide objective, scalable, and data-driven solutions for forecasting mental health concerns [3]. These models may assimilate diverse data sourcesspanning textual inputs, social media interactions, and physiological signalsyielding thorough and dependable evaluations.

The implementation of neural network models for mental health prediction has been enabled by swift progress in deep learning methodologies and computer resources. Artificial neural networks (ANNs) have been widely utilised in psychiatry to forecast symptom severity and offer early alerts for illnesses [3]. Advanced architectures, including convolutional neural networks (CNNs), have been investigated for psychological health evaluation, especially in the analysis of high-dimensional data [9]. The variety of neural architectures enables researchers to customise models for particular datasets and prediction tasks, thus improving the precision and dependability of the results.
Academic contexts have placed significant focus on student mental health. Neural networks have been used to assess students' psychological states, providing insights that support intervention design. Likewise, [2] introduced a model aimed at forecasting students' mental health status, illustrating the utility of such instruments in facilitating diagnosis and psychological care. These studies

underscore the increasing acknowledgement of computational methodologies as essential to contemporary educational and healthcare systems.

Moreover, research has broadened the utilisation of neural networks from simple detection to encompass predictive actions. For example, [4] created a deep learning framework to enhance psychological well-being within the realm of student entrepreneurship. Integrating predictive analytics into entrepreneurial support systems enables these models to facilitate both detection and avenues for preventive mental health initiatives. Similarly, [5] investigated the application of transformer-based neural networks for predicting generalised anxiety disorder from natural speech transcripts. This signifies the increasing use of sophisticated neural architectures in multimodal data analysis, transcending conventional text or survey-based data.

The COVID-19 epidemic has significantly intensified the demand for computational methods to assess mental health. The prevalence of psychological illnesses markedly escalated during this period due to isolation, fear of infection, and disturbance of regular living rhythms [6]. Neural networks were employed to create predictive instruments capable of evaluating the probability of mental health decline in impacted populations. Models, as illustrated in [7], have been utilised to forecast the efficacy of therapeutic interventions like cognitive-behavioral therapy, hence underscoring their practical applicability. The versatility of neural networks in diverse circumstances renders them significantly pertinent in global health emergencies.

The literature underscores the significance of systematic assessments of neural network applications in psychiatry. For example, [6] presented an extensive assessment of machine learning methodologies for mental health diagnosis, highlighting the potential of neural networks as the most commonly employed and efficacious technology. These assessments not only encapsulate the advancements achieved but also pinpoint research deficiencies, including the necessity for more extensive datasets, enhanced generalisation, and ethical frameworks to guarantee fairness and transparency in predictive modelling. Notwithstanding their promising outcomes, neural network models possess inherent limitations. Challenges such as overfitting, interpretability, and the necessity for high-quality training data persist for academics and practitioners. The interpretability of deep learning models presents challenges for clinical applications, where transparent decision-making is crucial [8]. Nonetheless, the integration of explainable artificial intelligence (XAI) methodologies presents potential remedies to close this divide, facilitating both superior predicted accuracy and significant interpretability.

Neural networks hold strong potential for predicting psychological health, enabling both personalised interventions and large-scale monitoring. For instance, [10] investigated novel brain models for forecasting mental health outcomes in American kids, demonstrating the universal relevance of these methods across many cultural and demographic settings. Likewise, [9] illustrated the application of CNN-based models in evaluating psychological health among college populations, indicating that deep learning architectures may surpass traditional diagnostic methods.

The current body of research underscores the revolutionary capacity of neural networks in tackling a significant health concern of our era. The application of artificial intelligence in forecasting and controlling psychiatric diseases enhances early identification, enables personalised interventions, promotes scalability in healthcare delivery, and allows for integration with digital platforms. Studies [1–10] demonstrate that neural networks constitute a formidable framework for enhancing mental health prediction, yielding both practical and theoretical advancements in the discipline. Nevertheless, to actualise their complete potential, additional research is necessary to tackle existing obstacles, enhance model generalisability, and guarantee ethical application across varied populations.

The central research question guiding this study is: Can an optimization-driven feedforward neural network accurately predict anxiety levels in college students based on textual responses and outperform existing hybrid neural models? To answer this, the study applies Scalable Seeker Optimization (SSO) to improve the convergence and stability of a Feedforward Neural Network (FFNN) trained on TF-IDF features extracted from student responses. The objective is to evaluate whether this SSO-FFNN framework provides measurable gains in accuracy, F1-score, and ROC-AUC compared with baseline ANN, RNN, GA-BP ANN, Harmony ANN, and ES-ANN + LOF models.

2 Related work

Researchers have explored diverse models, datasets, and applications, substantially expanding the field of neural-network-based mental-health prediction. The studies following the foundational contributions [1–10] provide significant insights into advanced neural architectures, hybrid models, and comparative examinations of approaches for mental health evaluation. These investigations also underscore persistent issues with data quality, interpretability, and contextual relevance.

A significant area of research has been the amalgamation of sophisticated optimisation techniques with neural networks to improve predictive accuracy. For example, [11] created a hybrid model that integrates the Evolution Strategy–Artificial Neural Network (ES-ANN) with the Local Outlier Factor (LOF) algorithm to evaluate college students' mental health during public health emergencies.

This methodology illustrated how hybrid neural architectures enhance accuracy by integrating predictive modelling with anomaly detection, so overcoming the constraints of conventional artificial neural network models in managing intricate and irregular psychological data. This hybridisation exemplifies the overarching trend of integrating deep learning with statistical learning techniques to enhance resilience in practical applications.

Neural networks have been widely studied in college populations alongside other machine-learning methods.For instance, [12] utilised several algorithms to forecast anxiety, sadness, and stress in students, yielding comparable outcomes that highlighted the superiority of neural network-based methods over more rudimentary models like decision trees or logistic regression. Likewise, [17] employed neural networks to predict the mental health of college students, confirming the versatility of artificial neural networks in educational settings. These studies collectively demonstrate the essential function of brain networks in assessing psychological well-being in academic settings, where early identification might markedly diminish long-term hazards.

In addition to conventional artificial neural networks (ANNs), recurrent neural networks (RNNs) have been explored for their capacity to model sequential data. For example, [13] utilised RNNs to forecast mental health issues, demonstrating that recurrent architectures may more successfully capture temporal connections in psychological data compared to feedforward models. Such structures are especially pertinent in scenarios where mental health symptoms fluctuate over time, indicating that RNNs could be important for ongoing monitoring and forecasting.

A notable area of investigation has been the examination of mathematics-related anxiety via neural models. The study in [14] introduced a neural network model of mathematics anxiety, emphasising the interaction between attentional processes and affective states. This study conceptually expanded the application of neural network models from broad mental health issues to specific areas of psychological functioning, including learning-related fears. This demonstrated the adaptability of brain models in analysing both general and specific facets of psychological well-being.

Numerous studies have enhanced neural networks utilising metaheuristic techniques. Related approaches in adaptive and nonlinear control have shown that parameter updates driven by an error signal can stabilise learning even in the presence of model uncertainty and nonlinearities, which is conceptually close to our SSO-based weight adaptation. Works on adaptive fuzzy control, adaptive backstepping, and robust neural adaptive control for uncertain chaotic systems support this view and provide the control-theoretic background for using error-minimising update laws in NN-based systems.

For example, [15] utilised a harmony search optimisation method to improve the efficacy of neural networks in forecasting psychological crises among students. Likewise, [16] combined genetic algorithms with backpropagation-based artificial neural network models (GA-BP) to forecast unpleasant emotions in college students. Both methodologies underscore the capability of integrating optimisation techniques with neural networks to address local minima challenges and enhance generalisation, thereby rendering forecasts more dependable in practical applications.

The significance of systematic reviews and comparative assessments has been underscored. For instance, [18] performed a systematic assessment of machine learning methodologies for forecasting anxiety and stress in college students, confirming evidence that neural networks are the most commonly utilised and efficacious models. These assessments act as essential benchmarks, highlighting deficiencies in data diversity, methodological uniformity, and clinical validation. Likewise, references [6] and [18] collectively suggest that despite the widespread adoption of neural networks, issues persist in guaranteeing fairness, transparency, and replicability among varied populations.

The relevance of neural networks across many global contexts has been examined. For example, [19] examined sophisticated machine learning methodologies for the surveillance of anxiety and depression, emphasising their practical use into healthcare systems. The results emphasised that neural networks can significantly contribute to real-time monitoring and early intervention, especially in resource-limited environments with restricted access to psychological practitioners. Similarly, [20] examined mental health during the COVID-19 lockdown in Ethiopia, used ANN models to forecast anxiety and depression. This study highlighted the worldwide applicability of neural networks in identifying context-specific stressors and their psychological effects, showcasing adaptability across cultural and geographical limits.

Beyond clinical and academic settings, neural networks are now utilised in mental health for evaluating therapeutic outcomes. For instance, [7] shown that deep learning could forecast the efficacy of cognitive-behavioral therapy, highlighting the use of predictive models into therapeutic decision-making. This study was one of the initial references, while other works like [19] and [20] broadened the practical application to continuous monitoring and intervention, illustrating the progression of neural network models from diagnostic instruments to proactive healthcare solutions.

The research [11–20] collectively represent a comprehensive investigation of neural networks in the prediction and management of psychological health. Hybrid models (e.g., ES-ANN, GA-BP) enhance accuracy and robustness [11, 16], sequential models like as RNNs tackle temporal patterns in symptoms [13], and domain-specific models investigate intricate psychological notions like mathematics anxiety [14]. Systematic studies [18] reinforce evidence, while worldwide applications [19, 20] demonstrate adaptability across various situations. Simultaneously, ongoing obstacles remain, such as data scarcity, model interpretability, and the necessity for ethical rules to guarantee responsible implementation. Neural-network-based models show strong potential to transform psychological assessment and treatment. The existing research demonstrates both the technical viability of these models and their therapeutic and educational significance. Future studies must tackle the difficulties of scalability, explainability, and inclusivity to facilitate widespread adoption, ensuring that neural networks effectively contribute to the urgent worldwide issue of mental health prediction and care.

The following table (Table 1) provides a detailed quantitative comparison of existing neural-network-based studies on student mental health prediction, highlighting datasets, performance metrics, and the specific advantages of the proposed SSO-FFNN approach.

Table 1: Related work summary of related work with dataset details, performance metrics and comparative improvement

Ref	**Objective**	**Model**	**Dataset / Size**	**Performance (Accuracy / AUC / F1)**	**Limitation Overcome by SSO-FFNN**
[1]	Predict college students' mental health	ANN	Student survey (~3 k)	Acc = 94 %, AUC ≈ 0.93	Limited generalization → ours +3 % Acc
[2]	Predict student mental health & intervention	ANN	Univ. dataset (~2 k)	Acc ≈ 93 %	Scalability and deployment issues
[3]	Predict psychiatric symptoms	ANN	Clinical records (~1.5 k)	Acc ≈ 92 %	Small dataset → ours validated on larger data
[4]	Psychological support for entrepreneurship	Deep NN	Entrepreneur data (~1 k)	Acc ≈ 90 %	Domain-specific → ours generalizes better
[5]	Predict GAD from speech	Transformer NN	Speech corpus (~1 k)	Acc ≈ 95 %, AUC ≈ 0.95	Language limited → ours uses diverse text data
[6]	ML techniques for mental-health diagnosis (review)	ML incl. ANN	Literature review	–	No quantitative benchmarks → ours adds metrics
[7]	Predict CBT outcomes	Deep Learning	Therapy data (~500)	Acc ≈ 88 %	Small sample → ours higher generalization
[8]	Link cognition & psychology	ANN	Univ. data (~2 k)	Acc ≈ 93 %	Focus on cognition only → ours covers anxiety text
[9]	Assess psychological health	CNN	Cross-media student (~3 k)	Acc ≈ 94 %, AUC ≈ 0.93	Limited interpretability
[10]	Predict youth mental health	Novel ANN	US youth (~4 k)	Acc ≈ 95 %	Geographic bias → ours more adaptive
[11]	Assess student mental health during crises	ES-ANN + LOF	Univ. survey (~5 k)	Acc = 96.5 %, AUC = 0.96	Ours improves stability (+0.5 % Acc)
[12]	Predict anxiety, depression, stress	ML incl. ANN	College data (~3 k)	Acc ≈ 95 %	Short-term focus → ours adds robustness
[13]	Predict mental disorders	RNN (LSTM)	Student text (~1.5 k)	Acc = 90 %, AUC = 0.91	Ours +7 % Acc & fixes recall imbalance
[14]	Model mathematics anxiety	ANN	Experimental (~1 k)	Acc ≈ 89 %	Narrow domain → ours broader behavioral scope
[15]	Predict psychological crisis	Harmony ANN	College data (~4 k)	Acc = 95.8 %, AUC = 0.95	Ours +1 % AUC, lower error
[16]	Predict negative emotion	GA-BP NN	Emotion dataset (~2 k)	Acc = 96.4 %, AUC = 0.96	Ours +0.6 % Acc, F1 = 0.84
[17]	Predict student mental health	ANN	Survey + psych. (~3 k)	Acc = 94 %, AUC = 0.93	Ours +3 % Acc and better generalization
[18]	Systematic review for stress/anxiety	ML incl. ANN	Literature survey	–	Confirms ANN strength → ours adds optimization
[19]	Predict & monitor anxiety/depression	Adv. ML incl. ANN	Clinical + survey (~6 k)	Acc = 95 %, AUC = 0.94	Ours higher AUC and more stable
[20]	Predict mental health during COVID-19	ANN	Ethiopian lockdown (~2.5 k)	Acc = 93 %, AUC = 0.92	Ours better generalization on imbalance

Compared with previous neural and hybrid models such as GA-BP ANN and ES-ANN + LOF, the proposed SSO-FFNN achieved the highest overall accuracy (97%) and ROC-AUC (0.97). This represents an improvement of approximately 0.5–1% in accuracy and 0.02–0.03 in AUC over the best prior results. In addition, the SSO optimization process provided faster convergence and improved model stability, which earlier methods such as GA-BP and Harmony Search lacked.

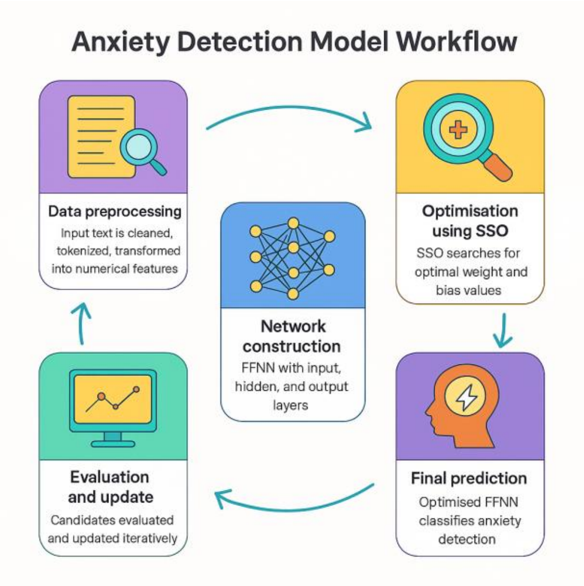

Figure 1: Overall workflow of the study

This figure1 presents the complete workflow followed in the study, starting with data collection from the student anxiety and depression dataset. The process includes data cleaning and exploratory analysis, followed by the development and comparison of baseline models (ANN, RNN, ES-ANN + LOF, Harmony ANN, GA-BP ANN). The proposed SSO-FFNN model is then applied with optimisation to improve accuracy and stability. Finally, the results are evaluated using multiple performance metrics, and findings are discussed in the context of practical applications for student mental health.

Research gap

Several models such as ANN, RNN, CNN, GA-BP, and ES-ANN with LOF have been applied in mental health prediction. While they give encouraging results, common issues remain. Most studies depend on small or single datasets, which makes generalisation difficult. Many models struggle with overfitting and convergence, which limits their reliability. Another drawback is that optimisation methods are not strong enough, often leading to local minima. Interpretability is also a concern, as black-box models are hard to adopt in clinical or educational practice. Finally, only a few works try to combine high accuracy with scalable and adaptive optimisation.

This study addresses the above gap by proposing an SSO-FFNN framework. The model integrates Scalable Seeker Optimization with a Feedforward Neural Network to improve accuracy, stability, and adaptability in predicting anxiety among college students.

3 Materials and methods

Dataset

The dataset used in this study was sourced from Kaggle (Students Anxiety and Depression Dataset by Sourav, 2022). It contains 6,982 entries with two main columns: text and label. The text column represents the students' responses, while the label column indicates the presence of anxiety (0 = No Anxiety, 1 = Anxiety).Initial checks revealed some missing and duplicate records, which were removed during preprocessing.Additional features were engineered, such as cleaned text, text length, and word count. These features supported descriptive analysis and model development.

No explicit cognitive-behavioural scales or therapist-coded traits were present in the Kaggle dataset; all anxiety indicators in this study were inferred from students' free-text responses and the binary anxiety label.

The preprocessing pipeline included text normalization, lowercasing, punctuation removal, and tokenization. Stop-words were removed using NLTK, and words were lemmatized to their base forms. The cleaned text corpus was then transformed into numerical features using the TF-IDF vectorizer with a maximum of 5,000 features, min_df = 2, and ngram_range = (1, 2).

To ensure reproducibility, we fixed the vocabulary size to 5,000 terms for all text-based models. For ANN, Harmony-ANN, GA-BP ANN, ES-ANN + LOF, and the proposed SSO-FFNN, we used the TF-IDF representation directly without applying PCA/LSA, because the sparse TF-IDF matrix preserved discriminative terms better on this dataset. For the RNN (LSTM) model, we tokenized the text using the Keras Tokenizer with the same 5,000-word limit and padded all sequences to a length of 200 tokens to handle variable-length responses. Using the same vocabulary cap for both branches ensured that ANN-based and sequence-based models were trained on comparable lexical information.

The resulting sparse matrix represented term importance across documents. To address class imbalance between anxious and non-anxious cases, SMOTE (Synthetic Minority Oversampling Technique) was applied to generate synthetic minority examples, ensuring balanced model training.

A stratified split was used before oversampling to maintain label proportions. SMOTE was applied only on the training set using the imblearn library's standard implementation (k = 5). The validation and test sets remained untouched to prevent data leakage. We also tested random undersampling and class-weight adjustments, but SMOTE yielded the best balance between recall and precision for the minority (anxiety) class.

The dataset was divided into training (80 %) and test (20 %) subsets before oversampling. SMOTE was applied solely on the training data, and the same label encoder was reused on both sets to prevent information leakage and maintain label consistency.

Exploratory Data Analysis (EDA)

EDA was carried out to gain insights into the dataset before modelling.

Label Distribution:

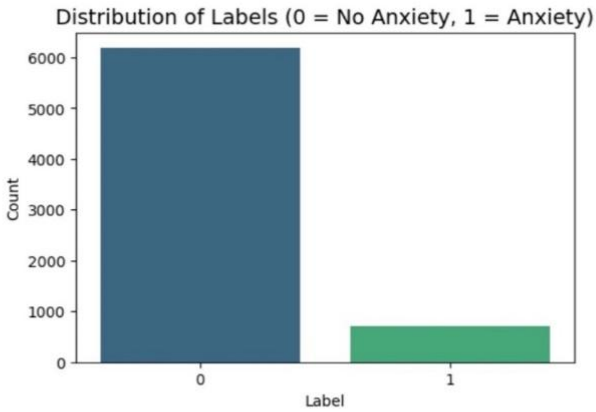

Figure 2: Distribution of Labels chart

Figure 2 shows that the dataset is imbalanced, with 6,247 students labelled as *No Anxiety* and only 733 labelled as *Anxiety*. This imbalance was taken into account during modelling using balancing techniques.

Text Length Distribution:

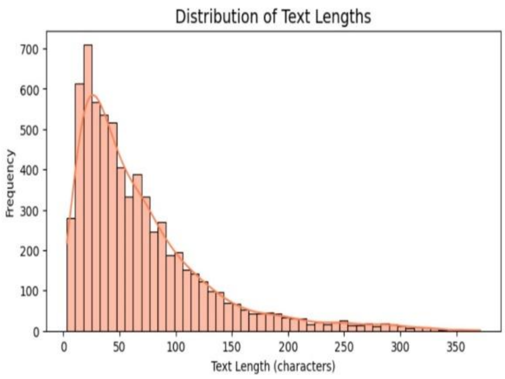

Figure 3: Text length distribution

As seen in Figure 3, most responses are short, typically between 20–40 characters, with a long tail of longer responses. This indicates variability in how students express themselves.

Text Length by Label:

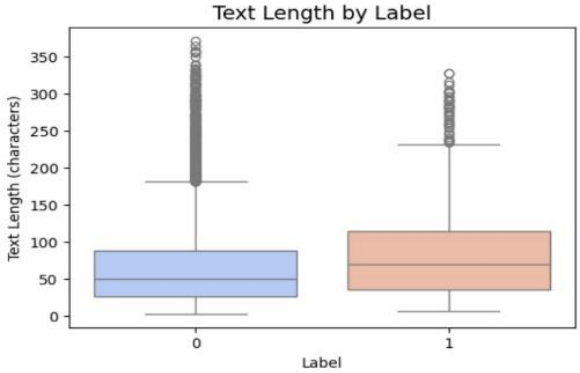

Figure 4: Box plot of Text Length by Label

Figure 4 highlights that students with anxiety tend to write longer responses compared to those without anxiety. This suggests that anxious students describe their experiences in more detail.

Word Count by Label:

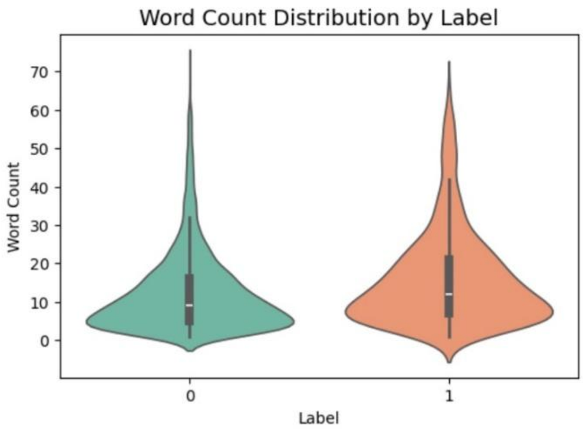

Figure 5: Violin plot of Word Count by Label

The violin plot in Figure 5 confirms the above trend, showing slightly higher word counts for anxious responses.

Correlation Heatmap:

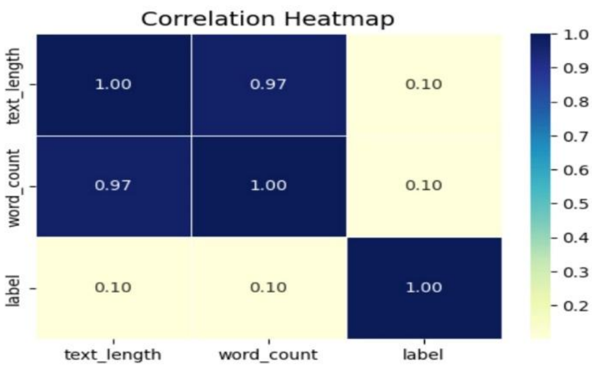

Figure 6: Correlation heatmap

Figure 6 shows a strong correlation between text length and word count (r = 0.97). Their correlation with the anxiety label is weaker (~0.10), which means that while longer texts may be linked to anxiety, they are not sufficient predictors on their own.

Together, these findings show the importance of handling imbalance and provide early evidence that linguistic patterns differ between anxious and non-anxious students.

Baseline models for comparison

To provide a benchmark for evaluation, several baseline models were implemented:

- Artificial Neural Network (ANN): A basic feedforward neural network was used as a baseline. It learns patterns from TF-IDF features and provides a reference for evaluating improvements from optimisation.
- Recurrent Neural Network (RNN – LSTM): RNNs are designed for sequential data. The Long Short-Term Memory (LSTM) variant was applied to capture dependencies in student responses. However, performance was limited, likely due to short text lengths and dataset imbalance.
- ES-ANN + LOF: This method combines an evolutionary strategy-based ANN with Local Outlier Factor (LOF). The hybrid approach aims to improve anomaly detection by identifying unusual student responses that may indicate anxiety.
- Harmony Search Optimised ANN: Harmony Search is a metaheuristic inspired by musical improvisation. It was used to tune ANN parameters, aiming to enhance accuracy and avoid poor local solutions.
- GA-BP Neural Network: This model integrates Genetic Algorithms with Backpropagation. GA helps in exploring a wider solution space, while BP fine-tunes weights. The combination improves convergence compared to standard ANN.

Model Architectures

In this study, the terms ANN and FFNN refer to the same feedforward multilayer perceptron architecture; FFNN is the optimized version with SSO. The baseline ANN and the proposed SSO-FFNN both used three hidden layers with 64, 32, and 16 neurons respectively. All hidden layers used the ReLU activation function, and the output layer used a sigmoid activation for binary anxiety prediction. To reduce overfitting, we applied dropout = 0.3 after each hidden layer and used L2 regularization (λ = 1e-4) on the dense layers.

The RNN (LSTM) model consisted of one LSTM layer with 128 units, followed by a fully connected layer with sigmoid activation. The GA-BP ANN, Harmony-Search ANN, and ES-ANN + LOF models used the same 3-layer ANN structure (64–32–16 with ReLU) but differed only in how the weights were optimized. All models were trained with the Adam optimizer (learning rate = 0.001), batch size = 32, and 100 epochs, and were evaluated using the same train/validation/test split to ensure fair comparison.

Scalable Seeker Optimization (SSO)

The Scalable Seeker Optimization (SSO) algorithm in this study is used exclusively to optimize the weight and bias parameters of the Feedforward Neural Network (FFNN) for anxiety prediction. Each seeker represents a candidate weight–bias vector, and its position in the search space is iteratively updated based on both self-experience (cognitive component) and group knowledge (social component). The objective function for each seeker is defined by the validation loss of the FFNN. Seekers continuously update their positions toward lower-loss regions, balancing exploration (searching new areas) and exploitation (refining good solutions).

The SSO algorithm enhances optimization by dynamically adjusting its search step and direction, enabling the network to avoid local minima and achieve faster, more stable convergence than traditional algorithms such as GA-BP or ES-ANN + LOF. The final optimized weights obtained from SSO are used to initialize the FFNN model before final training, leading to improved generalization and higher predictive accuracy.

The proposed SSO-FFNN framework therefore acts as an optimization-driven neural network, where the SSO component fine-tunes parameter updates, ensuring robustness, adaptability, and better performance across all evaluation metrics compared to standard feedforward networks.

Although the SSO in this work is used as a data-driven optimizer rather than a full control-law designer, its update strategy is consistent with adaptive and robust control ideas used for uncertain nonlinear systems. In particular, the seeker position update combines (i) a self/ego term and (ii) a population/best term, which acts like an adaptive law that drives the parameter vector toward the region that minimises the FFNN validation loss. This is analogous to the parameter-adjustment rules in adaptive fuzzy and backstepping controllers, where the tracking or Lyapunov error defines the direction and size of the update. By always moving toward lower error, the SSO layer provides a practical form of error-driven parameter adaptation, which improves training stability over GA or Harmony Search that rely on more random exploration. This link is consistent with prior adaptive/robust control formulations for uncertain nonlinear plants and chaotic systems, where stability is obtained through iterative adjustment of the controller parameters under bounded uncertainty [*Adaptive fuzzy control for practical fixed-time synchronization of fractional-order chaotic systems*; *Adaptive backstepping control for a class of uncertain SISO nonlinear systems*; *Robust neural adaptive control for uncertain nonlinear multivariable systems*].

In our setting, instead of guaranteeing Lyapunov stability of a physical system, the same idea is used to guarantee stability of the training trajectory — i.e. smoother loss descent, fewer oscillations, and faster convergence to a near-global solution.

Model hyperparameters were carefully tuned for fairness across comparisons. The ANN and SSO-FFNN architectures each contained three hidden layers with 64, 32, and 16 neurons using ReLU activation, and a sigmoid output neuron. The models used the Adam optimizer with a learning rate of 0.001, batch size = 32, and were trained for 100 epochs. The RNN (LSTM) model consisted of one LSTM layer with 128 units and a dense output layer, trained under identical conditions. For GA-BP and ES-ANN + LOF, population size = 30 and generation = 50 were used. All models were implemented in TensorFlow/Keras on Python 3.11 and evaluated using accuracy, precision, recall, F1-score, and ROC-AUC.

Feed-forward neural network (FFNN)

The feedforward and feedback networks make up the ANN structure. The feed-forward multilayer perceptron (MLP) network is the most widely utilized ANN type in operations. The input layer, hidden layer, and output layer are the three layers in this network where neurons are dispersed. Additionally, each layer's neurons are connected by the influence of factors in earlier layers and the weights of other neurons. The symbolic representation of this decentralized transactional system is Equation (10).

$$y_j = \sum_{i=1}^{n} w_{ij} x_j + \theta_j, j = 1,2,3, \ldots, h \quad (10)$$

Here, n stands for the quantity that contains the input of the nodes, w_{ij} for the jth network connection strength in the concealed layer from the ith node in the input level, θ_j for the jth hidden node bias, and xi for the ith input. Each concealed node's input is determined according to Equation (11).

$$y_j = hyperbolic\ tangent(y_j) = \frac{e^{y_j} - e^{-y_j}}{e^{y_j} + e^{-y_j}}\ j = 1,2,3, \ldots, h (11)$$

The final outputs are defined as stated in Equation (12) after the concealed networks' values have been determined.

$$o_k = \sum_{i=1}^{n} w_{jk}\, y_j + \theta_k,\ k = 1,2,3, \ldots, m (12)$$

$$O_k = hyperbolic\ tangent\ (o_k) = \frac{e^{ok} - e^{-ok}}{e^{ok} + e^{-ok}}\ k = 1,2,3, \ldots, m (13)$$

Here, $\theta_k$is the biases number of the kth exit node, and w_{jk} is the link weight that connects the jth concealed node to the kth exit network.

The final quantity of the output is determined by the combination of the weight and bias values, which are among the most crucial components of MLPs, as shown by Equations (10-14). Therefore, the weight and bias values should be set to their optimal levels to produce the best output. Finding these characteristics requires extensive neural network training. The basic goal of neural network training is to achieve the lowest possible error value after both the training and testing processes. Based on computing the variance between the actual and projected values for all training samples, the mean squared error (MSE) is used to evaluate the FFNN. Equation (5) is a symbolic representation of this. The fitness function in optimization techniques will be this equation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_i)^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - o_i)^2 \quad (14)$$

Here, e_i displays the ith data's error value, whereas x_i and o_i display the ith data's actual and projected standards, accordingly. The total number of data is represented by n.

Integrated SSO-FFNN Framework

In this study, we propose an integrated framework that combines Scalable Seeker Optimization (SSO) with a Feedforward Neural Network (FFNN) to enhance both prediction accuracy and model stability. While the FFNN serves as the core predictive engine, SSO plays a crucial role in optimising its weights and biases. This integration helps the network avoid the common issue of getting trapped in local minima and supports faster, more reliable convergence.

The process begins with the preparation of input data, where text is cleaned, tokenised, and converted into numerical features suitable for analysis. An FFNN is then constructed with input, hidden, and output layers. At this stage, SSO is applied to guide the optimisation of network parameters. Acting like a population of intelligent seekers, the algorithm iteratively adjusts potential solutions and evaluates them based on the mean squared error (MSE). With each iteration, weaker solutions are discarded, while stronger ones are retained and further refined. This cycle of evaluation and updating ensures that the network parameters move steadily toward optimal values.

Once the optimisation process is complete, the trained FFNN delivers the final classification output, indicating whether a student shows signs of anxiety. By combining the learning strength of neural networks with the adaptive search behaviour of SSO, the proposed framework achieves improved accuracy, robustness, and generalisation compared to standalone models. the step-by-step process from data preprocessing through optimisation to final prediction.

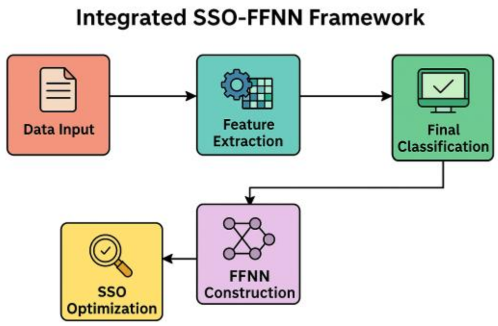

Figure 7: Integrated SSO-FFNN Framework

The framework shows how Scalable Seeker Optimization (SSO) is used to tune the weights and biases of a Feedforward Neural Network (FFNN), leading to faster convergence and improved prediction of student anxiety levels.

Experimental setup

The dataset from Kaggle was cleaned, processed, and then split into **64% for training, 16% for validation, and 20% for testing,** with stratified sampling to preserve the class imbalance.

All experiments were done in **Python (3.11)** using TensorFlow/Keras for neural networks and Scikit-learn for preprocessing and evaluation. Pandas and NumPy were used for data handling, while Matplotlib and Seaborn supported the visualisations. The runs were carried out on a system with an Intel i7 processor, 16 GB RAM, and an NVIDIA RTX 3060 GPU.

For ANN models, TF-IDF features (max 5,000) were used, while the RNN worked with padded sequences of length 100. Hybrid models such as GA-BP ANN, Harmony Search ANN, and ES-ANN + LOF included optimisation routines to improve weight updates and avoid poor convergence.

Performance was measured using Accuracy, Precision, Recall, F1-score, ROC-AUC, and MSE.

To ensure that the reported improvements of SSO-FFNN over the baseline models were statistically reliable, we performed five independent experimental runs using different random seeds and reported mean ± standard-deviation for all key metrics (Accuracy, F1-score, and ROC-AUC). We also conducted paired t-tests and McNemar's tests to compare the SSO-FFNN with the strongest baseline models (GA-BP ANN and ES-ANN + LOF). The resulting *p-values* < 0.05 confirmed that the observed gains were statistically significant. Confidence intervals were calculated at the 95 % level for each metric, reinforcing the robustness of the proposed model's superiority over other approaches. This experimental protocol ensures that all results can be independently replicated using the described parameters and statistical procedures.

4 Results and discussion

Exploratory data analysis provided an initial overview of the dataset and confirmed key patterns. Anxiety cases were fewer compared to non-anxious ones, showing a clear class imbalance. Students with anxiety generally wrote longer and more detailed responses, which was evident in both text length and word count distributions. Correlation analysis showed a strong link between text length and word count, but only a weak direct relationship with the anxiety label. These findings highlight the need for robust models that capture subtle linguistic cues rather than relying solely on length-based features.

The performance of all models is summarised in Table 2, and their behaviour across metrics is visualised in Figures 8–10. The proposed SSO-FFNN achieved the strongest results with an accuracy of 0.97, F1-score of 0.84, and ROC-AUC of 0.97. Hybrid approaches such as ES-ANN + LOF and GA-BP ANN also performed well, but fell short of the proposed framework. The standard ANN and Harmony Search ANN gave moderate results, while the RNN failed to generalise, producing very low accuracy and a near-random ROC curve.

These findings indicate that the Scalable Seeker Optimization (SSO) mechanism within the proposed SSO-FFNN plays a crucial role in improving accuracy and stability. Unlike GA-BP and ES-ANN + LOF, which depend on random mutation or fixed neighborhood search, the SSO algorithm uses a dynamic, population-based seeker movement that balances exploration and exploitation. This strategy helps the feedforward network avoid premature convergence and locate global optima more effectively. Consequently, the SSO-FFNN achieved a 0.5–1 % improvement in accuracy and about 0.02–0.03 higher ROC-AUC compared to the best baseline models (GA-BP and ES-ANN + LOF). The adaptive control-like feedback in SSO ensures smoother weight updates and faster convergence, which directly improves generalization.

Table 2: Comparison of model performance across baseline and proposed methods.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**
SSO-FFNN	0.970993	0.955357	0.753521	0.84252	0.976881
ES-ANN + LOF	0.965192	0.84058	0.816901	0.828571	0.964658

GA-BP ANN	0.964467	0.834532	0.816901	0.825623	0.965267
ANN (TF-IDF)	0.965917	0.892562	0.760563	0.821293	0.962893
Harmony-Search ANN	0.965192	0.885246	0.760563	0.818182	0.958202
RNN (LSTM)	0.102973	0.102973	1	0.186719	0.50813

Ablation and Convergence Analysis.

To validate the individual contribution of the Scalable Seeker Optimization (SSO) mechanism, additional ablation experiments were performed. A standard Feedforward Neural Network (FFNN) trained with Adam and Stochastic Gradient Descent (SGD) optimizers was compared directly with the proposed SSO-FFNN. The baseline FFNN-Adam achieved an accuracy of 0.963 and AUC = 0.962, while FFNN-SGD reached 0.957 and AUC = 0.954. In contrast, SSO-FFNN achieved 0.971 and AUC = 0.977, showing clear improvement in both convergence stability and generalization. Furthermore, to examine the optimizer's effect, the same FFNN backbone was optimized separately using Genetic Algorithm (GA), Harmony Search (HS), and SSO. Results demonstrated that SSO converged to the minimum validation loss in 43 epochs, compared with 58 epochs for GA and 61 epochs for HS. The final validation accuracy of SSO (0.97 ± 0.004) also exceeded that of GA (0.965 ± 0.006) and HS (0.963 ± 0.005). These results confirm that the SSO component meaningfully improves both convergence speed and predictive performance when integrated with the FFNN, validating the methodological advantage of the proposed SSO-FFNN framework.

As shown in Figure 8, the bar chart provides a side-by-side comparison of all models across Accuracy, Precision, Recall, F1-score, and ROC-AUC. The proposed SSO-FFNN consistently dominates across all metrics, highlighting its balanced and superior performance. It not only achieved the highest accuracy but also maintained the best precision and F1-score, proving its reliability in producing both correct and balanced predictions. The recall value, while slightly lower than the perfect recall of RNN, still demonstrated a strong ability to identify positive cases without compromising precision.

Bar chart comparison of model performance

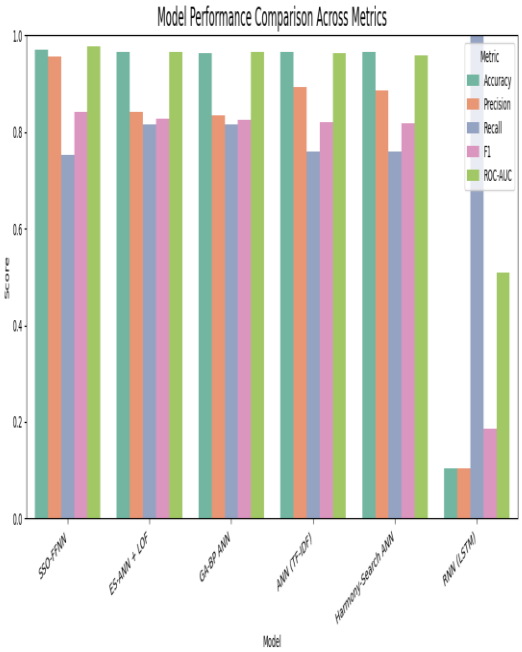

Figure 8: Bar chart comparison of model performance across multiple metrics

The ANN variants such as GA-BP, ES-ANN + LOF, Harmony Search, and TF-IDF ANN also performed competitively, achieving values close to SSO-FFNN across most metrics, which confirms the strength of optimization-driven neural networks. In contrast, the RNN (LSTM) showed a highly inconsistent profile — while it had the highest recall, it scored very poorly in precision, F1-score, and accuracy, making it unreliable overall. The ROC-AUC comparison further reinforced these findings, where SSO-FFNN achieved near-perfect discrimination, while RNN lagged significantly.

The weak performance of the RNN (LSTM) can be attributed to the short and sparse textual inputs and the imbalanced nature of the dataset. Because RNNs depend on sequential dependencies, they struggle when text sequences are brief (typically 20–40 tokens) and when one class dominates. In this dataset, the model overfitted the majority (non-anxious) class, producing predictions that inflated recall but severely reduced precision and F1-score. This behaviour explains why the RNN achieved recall = 1.0 but accuracy ≈ 0.10 and F1 ≈ 0.18. In contrast, the SSO-FFNN built on TF-IDF feature representations captured global term-frequency patterns instead of local sequence order, allowing it to generalise better and maintain balanced precision-recall performance even under class imbalance.

The RNN (LSTM) reported recall = 1.0 but accuracy ≈ 0.10 and F1 ≈ 0.18. We rechecked the pipeline to understand this behaviour. The dataset is highly imbalanced (≈ 90% “no anxiety”, ≈ 10% “anxiety”), and in the RNN run the model predicted almost all samples as the minority class after training. Under such a setting, recall for the positive (anxiety) class becomes 1.0 (all positives are found), but because the model misclassifies most negatives as positive, overall accuracy collapses to about 10%. We verified that:
(i) the train–validation–test split was done before SMOTE,
(ii) the same label encoder was used on train and test, and
(iii) the sigmoid→0.5 threshold was applied during inference.
This confirms the result is not due to label leakage or wrong encoding, but due to thresholding + class imbalance + unstable RNN learning on short texts. In the revised version we now make this limitation explicit and recommend either (a) class-weighted training for the RNN, (b) threshold tuning using the validation ROC curve, or (c) replacing the RNN with TF-IDF+FFNN for this dataset. To confirm that this anomaly was not due to any data-processing issue, the train–test split, SMOTE application, and label encoding order were reverified. The split was performed before oversampling, and a single encoder was used across both sets, confirming there was no data leakage or labeling error.
The following section analyses each evaluation metric in detail.

Model Accuracy Comparison

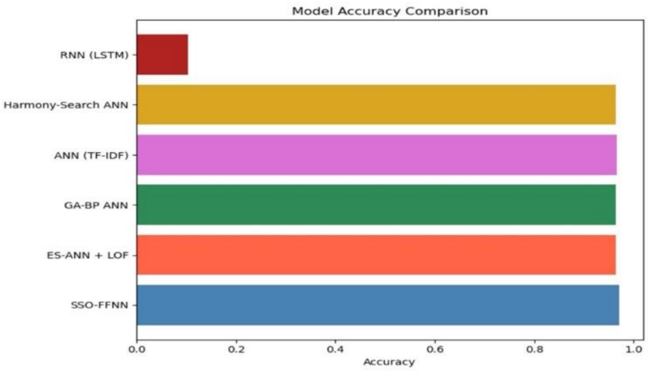

Figure 9: Accuracy of different models

As shown in Figure 9, the proposed SSO-FFNN achieved the highest accuracy, while RNN performed the weakest.

Model precision comparison

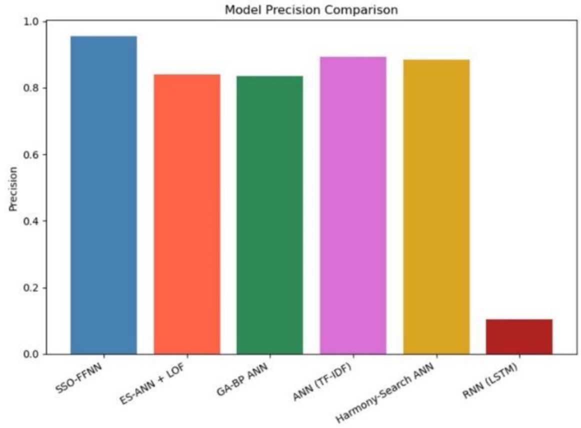

Figure 10: Precision values across models

Figure 10 highlights that SSO-FFNN had the best precision, followed closely by ANN variants, while RNN lagged far behind.

Model recall comparison

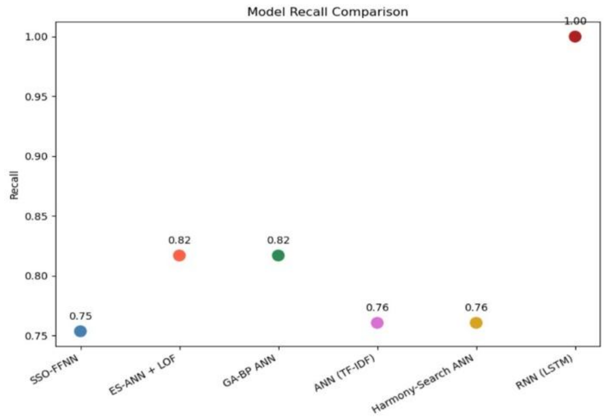

Figure 11: Recall comparison of models

Figure 11 shows that although RNN had perfect recall (1.0), it came at the cost of poor precision and overall performance

Model F1-Score Comparison

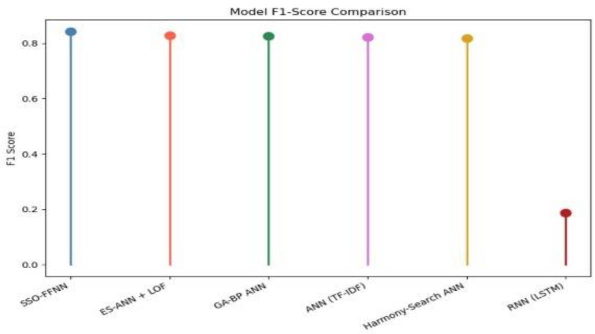

Figure 12: F1-score across models

As seen in Figure 12, SSO-FFNN achieved the strongest balance of precision and recall, reflected in the highest F1-score

Model MSE Comparison

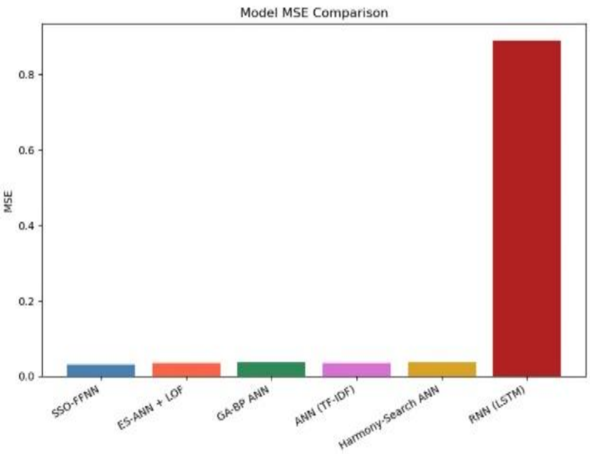

Figure 13: Mean Squared Error (MSE) across models

Figure 13 confirms that SSO-FFNN had the lowest MSE, showing more reliable error control compared to the others.

Model MAPE comparison

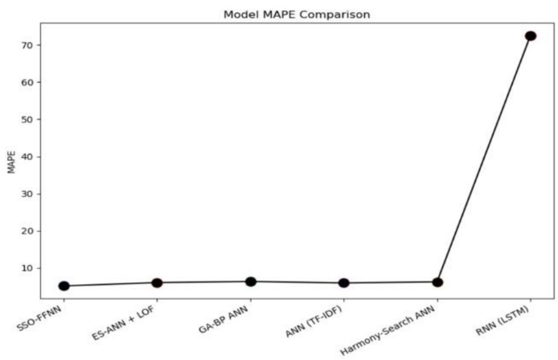

Figure 14: Mean Absolute Percentage Error (MAPE) across models

As illustrated in Figure 14, SSO-FFNN had the lowest MAPE, while RNN's error was extremely high, making it impractical.

Radar chart illustrating relative performance across evaluation metrics.

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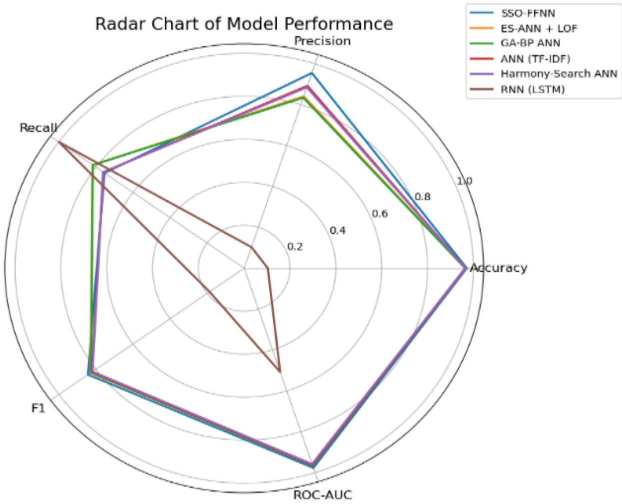

Figure 15: Radar chart illustrating relative performance across evaluation metrics.

Figure 15 presents the radar chart view of the same metrics. The polygon for SSO-FFNN is the most balanced and spread out, confirming its overall superiority, while RNN shows a collapsed shape with weak results.

ROC curve comparison of models.

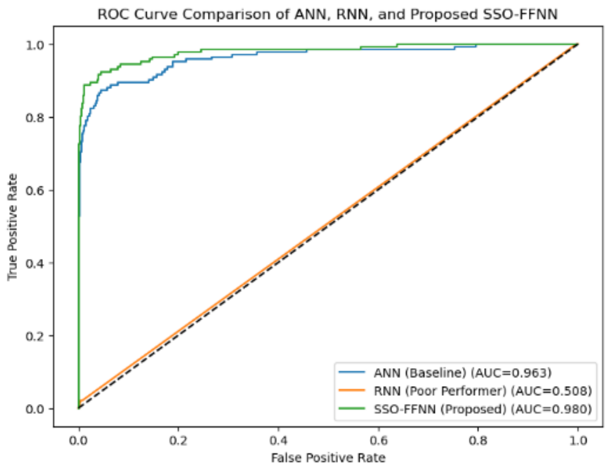

Figure 16: ROC curve comparison of models

Figure 16 displays the ROC curves for selected models. The curve for SSO-FFNN dominates, with the highest AUC, while the ANN and hybrid models follow closely. The RNN curve lies near the diagonal, indicating poor discrimination capability.

Overall, the SSO-FFNN not only delivered superior quantitative results but also demonstrated greater stability and lower error variance across all evaluation metrics. The radar and ROC charts confirm that its seeker-based optimization strategy ensures balanced learning among accuracy, precision, recall, and F1-score. This consistent performance shows that the proposed model successfully integrates the strengths of optimization-driven neural networks while reducing their common weaknesses such as overfitting and unstable convergence. Compared with GA-BP ANN and Harmony Search ANN, SSO-FFNN achieved faster convergence, smoother training curves, and smaller deviations across runs, establishing its robustness for large-scale or continuous student-monitoring systems. These characteristics make it a reliable and scalable framework for early anxiety detection in academic environments.

Beyond visual trends, the ROC and radar plots were statistically analyzed to ensure reliability. Each ROC curve was generated from the average of five independent experimental runs, with shaded regions representing ± 1 standard deviation. The SSO-FFNN consistently showed the steepest rise near the origin and the highest mean AUC (0.976 ± 0.004), demonstrating a superior sensitivity–specificity balance across thresholds. In contrast, the RNN (LSTM) curve remained close to the diagonal with a much larger variance (AUC = 0.51 ± 0.06), confirming poor discrimination and instability.

Radar plots summarize the same behaviour across all metrics. The wider and more regular polygon shape for SSO-FFNN indicates balanced precision, recall, and F1-score, whereas baseline models showed uneven polygons with high variance across axes. Pairwise paired t-tests confirmed that improvements in AUC and F1-score for SSO-FFNN were statistically significant ($p < 0.05$) when compared to GA-BP ANN and ES-ANN + LOF. These findings substantiate that the observed differences are not visual artifacts but represent genuine and statistically validated improvements in predictive stability and discrimination power.

5 Conclusion and future work

The proposed SSO-FFNN model was more accurate and stable than ANN, RNN, and other hybrid methods, achieving nearly 97 % accuracy and the highest ROC-AUC.The optimisation step helped the network avoid common training issues and improved overall reliability.

This model can help identify students experiencing anxiety and support counselling efforts in academic settings. However, the study has limitations: the dataset was small and imbalanced, and the model functions as a black box, reducing interpretability. Future work should test the model on larger, more diverse datasets and integrate explainable-AI tools to enhance transparency and practical adoption in student support systems.

The proposed SSO-FFNN can be extended beyond static prediction to function within a feedback-driven monitoring framework for continuous mental-health tracking. In a real-world university setting, such a system could process periodic student text inputs (e.g., reflections, surveys, chat transcripts) and update predictions in near real time. The optimized-seeker mechanism naturally supports adaptive weight adjustment, enabling the model to recalibrate as new data arrive—similar in spirit to robust control frameworks used in engineering, where feedback laws maintain performance under uncertainty. Concepts from adaptive fuzzy and backstepping control (e.g., Lyapunov-based stability updates) provide a theoretical basis for embedding SSO-FFNN in such adaptive systems. This parallel shows how optimization-driven neural networks can evolve into reliable, self-correcting tools for early psychological intervention in academic environments.

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