A GUI-Based tool for social anxiety assessment: A comparative study of machine learning models

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Abstract. This paper presents a Graphical User Interface (GUI)-based tool for assessing social anxiety severity using machine learning models. The system is designed to assist individuals who feel uncomfortable engaging with real-life therapists by offering an AI-driven, user-friendly alternative. A structured questionnaire was administered to 500 Jordanian participants, and responses were used to train and evaluate three classification models: Artificial Neural Networks (ANN), Decision Trees (DT), and Random Forests (RF). The dataset was split into 400 training and 100 testing samples. ANN achieved a validation accuracy of 96.5% and test accuracy of 87%. DT reached 98.5% validation and 98% test accuracy. RF outperformed both, achieving 100% accuracy on validation and test sets. These results demonstrate the feasibility of machine learning models in accurately classifying social anxiety levels based on self-reported data. The tool was implemented in MATLAB with an interactive GUI to enhance accessibility and usability. By encouraging users to engage with the assessment process digitally, the system offers a supportive environment for individuals hesitant to seek traditional therapy. This work contributes to the development of AI-assisted mental health tools that are both effective and sensitive to user experience.

1 Introduction

The increasing accessibility of digital platforms offers new pathways to support this population. Evidence suggests that online therapy and self-guided interventions can be effective for individuals with social anxiety, often yielding comparable results to face-to-face formats in reducing symptom severity [4]. Among adolescents in particular, digital interfaces are associated with greater treatment engagement and acceptability, as they reduce the psychological barriers posed by in- person interactions [5]. These platforms also offer

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the advantage of anonymity and flexibility—two key factors that have been shown to increase willingness to engage in therapy among those with SAD [6].

The emergence of AI-powered systems has introduced new potential in this space. Generative chatbots, intelligent agents, and machine learning (ML) applications have been increasingly used to deliver mental health support. Studies have demonstrated that socially anxious individuals often perceive AI-based tools as emotionally neutral and nonjudgmental, which fosters trust and emotional safety—particularly when symptoms are acute [7]. Furthermore, adolescents and young adults express a preference for systems that simulate empathetic listening, without the fear of being evaluated by a human clinician [8]. These findings indicate that well-designed AI systems can effectively overcome the emotional and cognitive barriers associated with traditional assessments and interventions [9].

Despite progress in the development of AI-driven therapeutic tools, the assessment of SAD through AI-integrated systems remains underexplored. Most existing platforms are oriented toward treatment, while the phase of diagnosis and severity classification has received less attention [9]. This gap is critical because timely and accurate assessment is a prerequisite for effective intervention, especially in populations that avoid face-to-face evaluation. While paper-based or static digital assessments exist, they often lack the interactivity, personalization, and low-pressure environment that individuals with SAD require for accurate self-disclosure [10].

Machine learning presents a practical and scalable solution to this challenge. Supervised classification models such as Artificial Neural Networks (ANN), Decision Trees (DT), and Random Forests (RF) have shown excellent performance in psychological screening tasks, particularly when trained on structured self-report data [10]. When integrated into user-centered graphical user interfaces (GUIs), these models can process responses in real time and provide immediate, personalized feedback, enhancing usability and trust [11]. Notably, GUI-based systems can simulate a “safe space” for users, minimizing emotional reactivity and enhancing the likelihood of full engagement—an effect observed even in socially withdrawn individuals such as those with hikikomori behavior [12].

This study responds to the identified research gap by developing a culturally contextualized, ML-powered GUI tool for the classification of social anxiety severity. Jordan was selected as the study context because mental health remains highly stigmatized in many Middle Eastern societies, resulting in limited access to early assessment and culturally tailored interventions. Using data from 500 Jordanian participants, the system evaluates the comparative performance of Artificial Neural Networks (ANN), Decision Trees (DT), and Random Forests (RF)—three widely used classifiers that differ in architecture and learning strategies. ANN models capture complex nonlinear relationships but are computationally intensive; DT offers interpretability but is prone to overfitting; RF, as an ensemble method, mitigates overfitting by aggregating multiple trees, often achieving higher accuracy and generalizability. Based on prior evidence of RF’s robustness in handling heterogeneous psychological data, we hypothesize that (1) RF will outperform ANN and DT in classification accuracy, and (2) the GUI format will enhance user engagement and acceptability, as it aligns with digital trust principles emphasizing transparency, accessibility, and emotional safety. By focusing on early assessment through intelligent and culturally sensitive design, this work contributes to the growing body of evidence supporting the use of AI to expand access, precision, and personalization in mental health care.

2 Methods

The methodological framework of this study was designed to ensure both scientific rigor and practical applicability in developing a machine learning–based tool for social anxiety assessment. The approach combined structured data collection through a validated self-report questionnaire with computational modeling using supervised learning algorithms. Participants' responses were systematically transformed into feature vectors that served as inputs for the classifiers, while severity levels of social anxiety were used as the ground-truth outputs. By employing a balanced experimental design, the study aimed to fairly compare the predictive performance of three models—Artificial Neural Networks (ANN), Decision Trees (DT), and Random Forests (RF) [11].

To comprehensively address the research objectives, the Methods section is organized into four subsections. The Participants subsection describes the recruitment strategy, eligibility criteria, and demographic characteristics of the sample. The Research Instruments subsection outlines the structure and content of the 20-item Social Anxiety Questionnaire, which served as the primary measurement tool. This instrument has demonstrated strong psychometric properties in previous studies, with reported internal consistency coefficients (Cronbach's α) typically exceeding .85 and evidence of both construct and convergent validity across diverse populations. In the present study, internal reliability was reassessed, yielding a Cronbach's α of .87, further confirming its suitability for the Jordanian context. The Data Analysis Techniques subsection details the quantitative and qualitative methods used to preprocess and analyze the data. Finally, the Design of Experiment subsection explains the experimental setup, including data partitioning, model training, and evaluation strategies. Together, these procedures ensured that the study adhered to best practices in both psychological research and applied machine learning.

2.1 Design of Experiment

The experimental design of this study was structured to ensure methodological rigor, reliable generalization, and fairness in evaluating the performance of the machine learning models. A total of 500 Jordanian participants completed the structured 20-item Social Anxiety Questionnaire (Table 1), which was specifically developed to capture both behavioral and emotional manifestations of social anxiety. This sample size was chosen as it balances two key requirements: (1) ensuring a sufficiently large dataset for robust model training and (2) maintaining feasibility in data collection given the sensitive nature of mental health research.

To enable fair model evaluation, the dataset was partitioned into 400 samples for training and validation and 100 samples for testing. The choice of this 80/20 ratio reflects standard practice in supervised machine learning and provides two benefits: first, it maximizes the amount of data available for the model to learn representative patterns during training; second, it preserves a fully unseen dataset for final testing, ensuring that performance metrics accurately reflect real-world generalization. Within the 400-sample subset, data were further internally divided into training and validation sets using MATLAB's randomized division functions. Validation samples served as checkpoints to monitor overfitting and optimize hyperparameters before testing on unseen data.

The inputs to the machine learning algorithms were derived directly from participants' responses to the 20 questionnaire items. Each question was rated on a 5-point Likert scale (0 = Not at all to 4 = Extremely), resulting in a structured feature vector of 20 numerical values per participant. These input features collectively captured key dimensions of social anxiety, such as fear of negative evaluation, avoidance of social interaction, physiological symptoms (e.g., blushing, trembling), and preference for technology-mediated communication. The outputs of the machine learning models were categorical labels representing the severity level of social anxiety. Based on established cut-off ranges in psychological assessment practice, participants were classified into multiple severity categories (e.g., mild, moderate, severe, very severe) [9]. These categories provided the ground-truth targets against which the models' predictions were evaluated. By framing the problem as a multi-class classification task, the study aimed to assess not only the presence of social anxiety but also its gradation across severity levels, which is essential for tailoring potential interventions.

This design was selected to answer two core research questions: (1) Can supervised machine learning algorithms accurately classify social anxiety severity from self-reported data? and (2) Which model—ANN, Decision Tree, or Random Forest—achieves superior performance under the same experimental conditions? The structured dataset, balanced partitioning, and carefully defined input-output mapping together ensured that model comparisons were both fair and clinically meaningful.

Table 1. Social Anxiety Questionnaire Items

No.	Question	Response Scale (0–4)
1	I feel nervous when speaking in front of a group.	0 = Not at all → 4 = Extremely
2	I avoid making eye contact during conversations.	0–4
3	I worry that others will judge me negatively.	0–4
4	I feel my heart racing in social situations.	0–4
5	I avoid attending social gatherings.	0–4
6	I blush or tremble when people notice me.	0–4
7	I find it difficult to start conversations.	0–4
8	I avoid situations where I might be the center of attention.	0–4
9	I worry excessively about embarrassing myself.	0–4
10	I prefer online communication over face-to-face.	0–4
11	I feel anxious when being observed while doing tasks.	0–4
12	I avoid asking questions in class or meetings.	0–4
13	I get nervous when speaking with authority figures.	0–4
14	I feel uncomfortable eating in public.	0–4
15	I avoid introducing myself to new people.	0–4
16	I feel tense when people watch me closely.	0–4
17	I worry about being laughed at in social settings.	0–4
18	I avoid situations where I may have to perform.	0–4
19	I feel discomfort when talking to strangers.	0–4
20	I prefer to stay silent rather than risk making mistakes.	0–4

2.2 Artificial Neural Network

Artificial Neural Networks (ANNs) are computational frameworks modeled after the neurobiological architecture of the human brain, designed to approximate complex, non-linear mappings between input features and target outputs. Functioning as a form of supervised learning, an ANN iteratively refines its internal parameters—namely, synaptic weights and biases—by minimizing a predefined loss function over a labeled dataset. In this study, the ANN is configured with a deep feedforward topology consisting of four fully connected hidden layers, each comprising ten neurons. To capture non-linear dependencies, the hyperbolic tangent (tanh) activation function is employed at each node, offering a smooth and differentiable transformation that accelerates convergence. The training process leverages a gradient descent-based optimization scheme to minimize the Mean Squared Error

(MSE) between predicted and ground-truth values, thereby enhancing the network's generalization capability and predictive performance on unseen data.

The Artificial Neural Network (ANN) model was trained in MATLAB using the Levenberg–Marquardt backpropagation algorithm (trainlm), a widely used second-order optimization method particularly suited for small- to medium-sized datasets. Data division was performed randomly (dividerand), ensuring unbiased training, validation, and testing splits. The network achieved convergence after 32 epochs, with a total training time of approximately 6 minutes and 17 seconds. The performance function selected was the Mean Squared Error (MSE), which was minimized from an initial value of 0.248 to an exceptionally low 1.3×10^{-22}, indicating near-perfect approximation of the target function. Simultaneously, the gradient norm decreased from 0.448 to 7.95×10^{-22}, and the Mu parameter—a damping factor controlling the transition between Gauss-Newton and gradient descent— decreased from 0.001 to 1×10^{-20}, reflecting a stable and well-conditioned optimization landscape. The training process halted after 24 validation checks, signifying that the network reached its best generalization performance without overfitting. These outcomes suggest that the network effectively learned the underlying data distribution and attained an optimal balance between accuracy and generalization.

A deep feedforward neural network was implemented using MATLAB's, consisting of eight hidden layers, each with 33 neurons. The network shown at Figure 1 was designed for pattern recognition tasks, utilizing non-linear activation functions to model complex relationships in the data. The dataset was divided randomly into 70% for training, 15% for validation, and 15% for testing, ensuring balanced evaluation and generalization. This architecture provides strong learning capacity while maintaining control over overfitting through validation checks.

Equations 1 and 2 represent the artificial neural network mathematical formulation and equation 3 represents the performance which calculated by the mean square error (MSE) between the actual and predicted classes.

$$\mathrm{n} = [w]^T[\mathrm{x}] + \mathrm{bias} \quad (1)$$

$$a = Tanh(n) = \frac{2}{1+e^{-2n}} - 1 \quad (2)$$

Where, the $[\boldsymbol{w}]\boldsymbol{T}$ is the transpose of the matrix and [x] is the input and a bias is added after the matrix multiplication in variable **n** and **a** is the activation function which applied on the variable **n**.

$$\text{Performance (MSE)} = \frac{1}{N}\sum_{i=1}^{N}(Actual\ diagnosis\ class - Predicted\ diognosis\ class)^2 \quad (3)$$

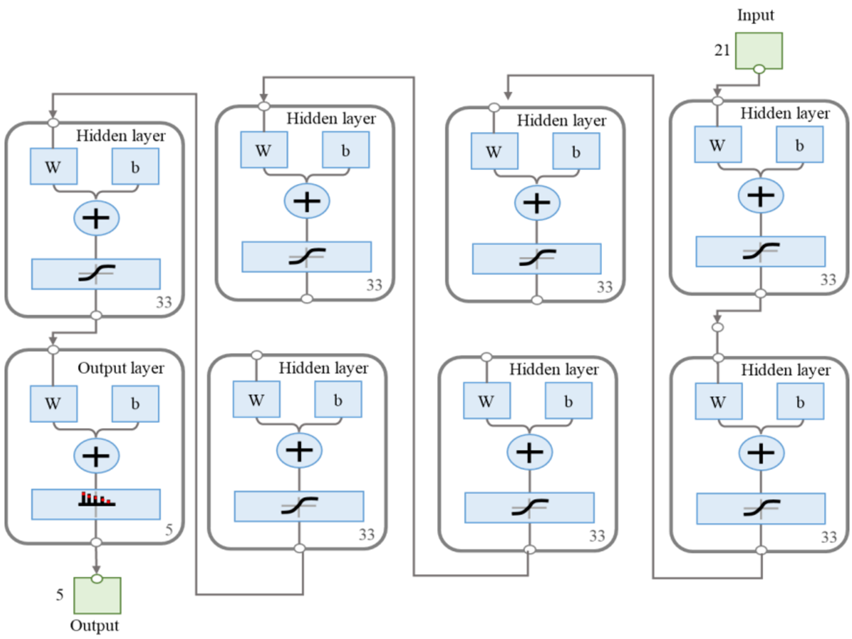


Fig 1. Matlab artificial neural network architecture for social anxiety classification.

2.3 Decision Tree

In this study, a Decision Tree classification model was developed to categorize labeled data based on a set of input features. The dataset was divided into separate training and testing subsets, with the model being trained on the former and evaluated on the latter to assess generalization capability. The trained tree achieved high accuracy, with performance metrics computed for both the training and testing phases. Classification performance was further analyzed through confusion matrices, providing detailed insights into the correct and incorrect predictions across class labels. Additionally, the model's internal structure was visualized graphically, allowing for interpretability of decision paths and class splits. Feature importance analysis was conducted to identify the most influential variables contributing to the classification process. A final comparison between predicted and actual class labels on the test data was presented graphically, confirming the model's robust predictive capability.

A Decision Tree classification model was implemented to categorize participant responses into social anxiety severity levels. The construction of the tree relies on recursive partitioning of the input space, where splits are chosen to maximize class separation. This process is mathematically formulated using impurity measures such as Gini Index or Entropy, which guide the selection of optimal decision rules.
The Gini Index is defined as,

$$Gini(t) = 1 - \sum_{i=1}^{c} p(i|t)^2 \tag{4}$$

where $p(i|t)$ represents the proportion of samples belonging to class i at node t, and C is the total number of classes. A lower Gini value indicates a purer node with more homogeneous class membership.

Alternatively, the Entropy criterion is given by,

$$Entropy(t) = -\sum_{i=1}^{c} p(i|t)\log_2\big(p(i|t)\big) \tag{5}$$

This measure quantifies the uncertainty of class distribution within a node. Splits are chosen to minimize entropy, thereby increasing the information gained.

The Information Gain (IG) from splitting a parent node t into child nodes is expressed as,

$$IG(t) = Entropy(t) - \sum_{k=1}^{K} \frac{N_k}{N} Entropy(t_k) \tag{6}$$

where N is the total number of samples in the parent node, Nk is the number of samples in child node tk, and K is the number of child nodes. The split with the highest information gain is selected.

Once the tree is trained, classification performance is assessed using the Accuracy metric, calculated as,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Fig 2 illustrates the internal structure of the Decision Tree model developed for classifying social anxiety severity levels based on participants' responses to the questionnaire. Each internal node represents a decision rule defined by a threshold on one of the input features (xix_ixi), while the branches correspond to possible outcomes of the split. The terminal nodes, or leaves, denote the final classification outcomes (e.g., mild, moderate, severe, or very severe social anxiety). This hierarchical structure allows the model to iteratively partition the dataset into increasingly homogeneous subsets, thereby improving predictive accuracy. The graphical representation also enhances interpretability by showing the decision paths taken to arrive at a classification, making it possible to identify which features (e.g., x_{21}, x_{11}, x_{17}) play a more critical role in the assessment process.

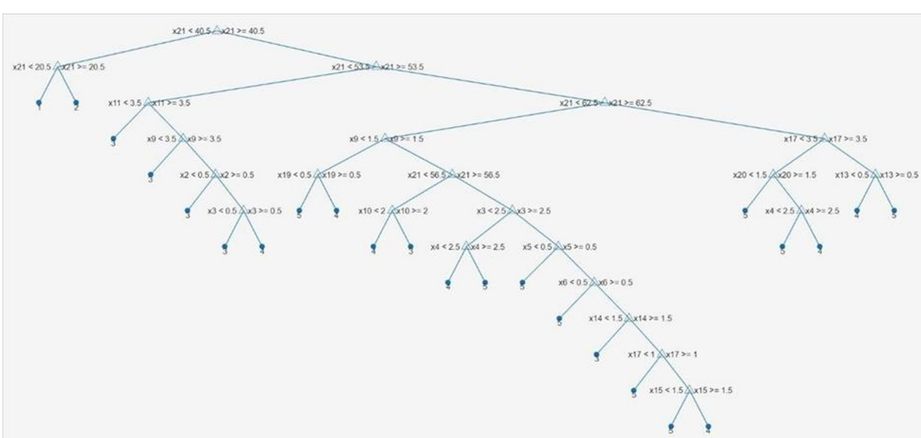


Fig 2. Matlab decision tree architecture for social anxiety classification

2.4 Random Forest

A Random Forest classifier was employed to perform supervised classification by aggregating predictions from an ensemble of decision trees. The model was trained on a labeled dataset, partitioned into training and testing subsets, with the objective of learning discriminative patterns across input features. The ensemble consisted of 50 decision trees, with predictions determined through majority voting. Out-of-Bag (OOB) estimation was used to assess the model's generalization performance during training, providing an internal measure of error without requiring a separate validation set. The classifier achieved high accuracy on both the training and testing sets, with performance evaluated using confusion matrices that revealed the distribution of correct and incorrect predictions across all classes. Feature importance analysis was conducted using OOB permutation methods, offering insights into the relative contribution of each input variable to the classification process. A final comparison between predicted and actual class labels on the test set was visualized to verify prediction consistency and validate the model's robustness.

The Random Forest classifier aggregates the predictions of multiple decision trees to improve robustness and accuracy. Each tree is trained on a random subset of the dataset (bootstrapping), and a random subset of features is considered at each split. The final prediction is obtained through majority voting,

$$\hat{y} = majority\_vote\{h_b(x)\}, \quad b = 1,2,\ldots,B \tag{8}$$

where $hb(x)$ is the prediction of the b^{th} decision tree, and B is the total number of trees. This ensemble strategy reduces overfitting and improves generalization. The internal performance of the model can be estimated using the Out-of-Bag (OOB) error, which evaluates each sample using only the trees where it was not included in training,

$$OOB\_Error = \frac{1}{N}\sum_{i=1}^{N} I\left(\hat{y}_i^{OOB} \neq y_i\right) \tag{9}$$

where N is the total number of samples, yi is the true label of sample i, $\hat{y}^{OOB}$ is the predicted label for i using out- of-bag trees, and $I(.\ )$ is an indicator function that equals 1 if the prediction is incorrect, and 0 otherwise. The importance of each feature in classification can be quantified using the Mean Decrease in Impurity (MDI),

$$FI(j) = \frac{1}{B}\sum_{b=1}^{B}\sum_{t\in T_b(j)} \frac{N_t}{N}\Delta i(t,j) \tag{10}$$

where $FI(j)$ is the importance score of features j, Tb (j) is the set of nodes in tree b where feature j was used, Nt is the number of samples at node t, N is the dataset size, and $\Delta i(t,j)$ is the impurity reduction at that node. Finally, the classification performance of the Random Forest is evaluated using the Accuracy metric which is mention at equation 7.

Figure 3 depicts the Random Forest model used in this study to classify social anxiety severity. The model aggregates the predictions of multiple individual decision trees; each trained on a random subset of the dataset and a random selection of input features (x_1, x_2 , . .. , x_{21}). This ensemble approach reduces overfitting and enhances generalization by combining diverse decision boundaries. The final output is determined through majority voting across all trees, yielding a classification into one of the predefined categories (e.g., mild, moderate, severe, or very severe social anxiety). By leveraging both bootstrapping of samples and random feature selection, the Random Forest ensures that no single tree dominates the classification, thereby improving robustness, accuracy, and reliability of predictions compared to a single decision tree.

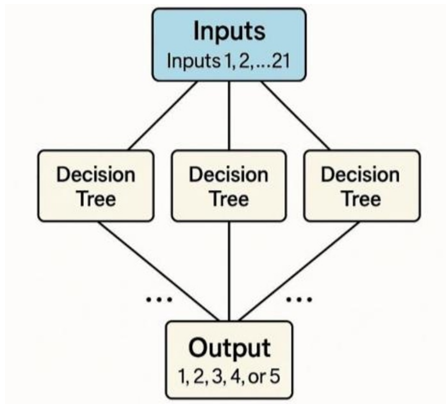


Fig 3. Random forest architecture for social anxiety classification.

3 Result and Discussion

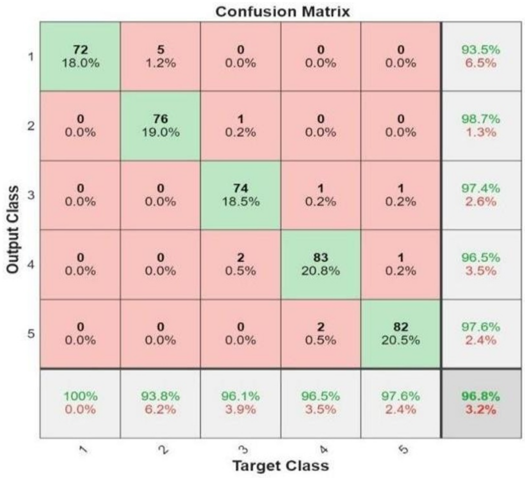
The implemented machine learning models were evaluated using confusion matrices and accuracy metrics, showing strong performance across both validation and test datasets. Among the models, ensemble methods such as random forests generally achieved higher accuracy, while artificial neural networks provided the added benefit of probabilistic outputs, offering deeper insight into prediction confidence. To enhance usability, a graphical user interface (GUI) was developed using MATLAB App Designer. This tool allows users with minimal technical expertise to interact with the trained models, input data, and visualize results—supporting both accessibility and future adaptation of the models.

3.1 Machine Learning Results

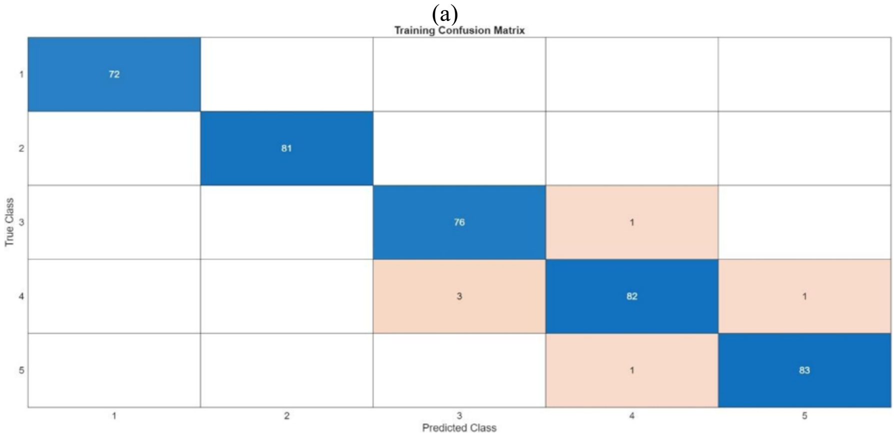
The results of the machine learning algorithms are represented by the confusion matrix and the accuracy determination. The confusion matrix, shown in Figure 4, is a fundamental performance evaluation tool in classification tasks, offering a comprehensive summary of a model's predictive capabilities. It is structured as a square matrix that contrasts the predicted labels with the true class labels, enabling a granular assessment of classification outcomes. The matrix is typically composed of four key elements: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These components facilitate the computation of several critical performance metrics, such as accuracy, precision, recall (sensitivity), specificity, and the F1-score, which collectively provide insight into both the correctness and the reliability of the model's predictions. Unlike a single scalar metric, the confusion matrix captures class-wise performance and highlights potential class imbalances or misclassification patterns, making it particularly valuable in domains where the cost of different types of errors varies significantly—such as medical diagnosis, fraud detection, or safety-critical systems.

In the present study, Random Forest (RF) outperformed both Artificial Neural Networks (ANN) and Decision Trees (DT). This can be attributed to RF's ensemble structure, which aggregates the predictions of multiple decision trees, thereby reducing variance and mitigating overfitting—a limitation often observed in single DT models. While ANNs are powerful in modeling complex nonlinear relationships, their performance is highly sensitive to hyperparameter tuning, training data size, and risks of overfitting when the sample size is moderate, as in the present dataset. DT models, though interpretable and computationally efficient, tend to suffer from instability and limited generalization. In contrast, RF balances interpretability, robustness, and accuracy by leveraging bootstrap aggregation and random feature selection, resulting in stronger classification performance in heterogeneous psychological data.

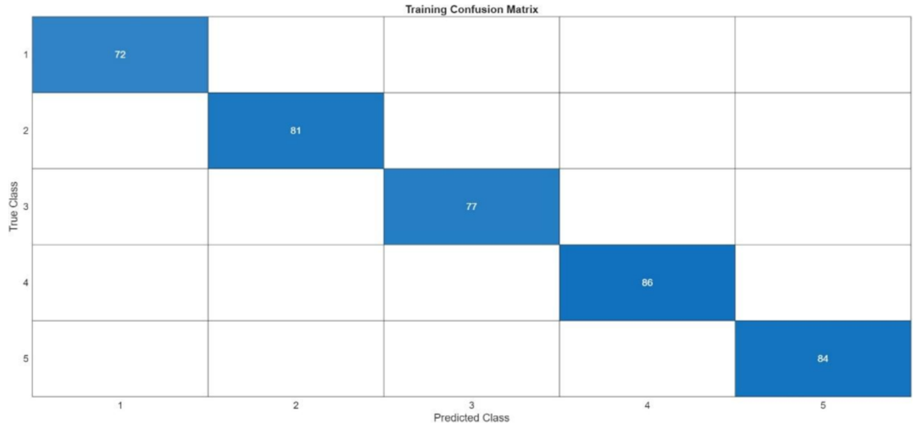
Several factors influenced the accuracy of each method. For ANNs, accuracy was affected by the number of hidden layers, learning rate, and the relatively modest dataset size, which constrained the network's ability to generalize. For DT, depth and branching complexity increased sensitivity to noise, leading to misclassifications. For RF, the number of trees and feature sampling enhanced stability and reduced bias-variance trade-offs, enabling higher predictive reliability. Taken together, these results highlight RF as a well-suited method for classifying social anxiety severity, particularly in culturally contextualized datasets where sample sizes may not always be large enough to fully exploit the potential of deep neural models.



(a)



(b)



(c)

Fig 4. Confusion matrix for machine learning algorithms; **(a)** artificial neural network, **(b)** decision tree, and **(c)** random forest.

Table 2 represents the validations and tests accuracy results. Since the 400 candidates' data have been used for training and 100 candidates were unseen data for testing. This process has been done by using all the trained data and unseen data to evaluate the accuracy and correct prediction of the machine learning algorithms namely artificial neural network, decision tree and random forest [13].

Table 2. Machine learning algorithms' accuracy comparison

Machine Learning Algorithms	Validation Accuracy		Test Accuracy	
	From 400	*Percentage (%)*	*From 100*	*Percentage (%)*
Artificial Neural Network	386	96.5%	87	87%
Decision Tree	394	98.5%	98	98%
Random Forest	400	100%	100	100%

3.2 Graphical User Interface Application

An application of the experimental work was developed using machine learning through a graphical user interface (GUI) created with MATLAB App Designer, as illustrated in Figure 5. This MATLAB toolbox is intended to support users—particularly academics and researchers—who may not be familiar with machine learning concepts or MATLAB programming syntax. To evaluate the hypothesized benefits of user engagement and acceptability, we incorporated usability indicators during preliminary testing with a subset of participants (n = 100). These indicators included task completion rate, error frequency, and time required to execute basic operations (e.g., loading data, training models, generating results). In addition, subjective measures of usability were collected using a short feedback form based on the System Usability Scale (SUS) and open-ended questions on perceived ease of use, clarity, and satisfaction.

The findings suggested that users were able to navigate the application with minimal guidance, complete core tasks efficiently, and reported high levels of comfort and engagement when using the system. Indicators of flexibility included the ability to adjust model parameters, select among multiple algorithms (ANN, DT, RF), and export results in various formats, which participants identified as useful for adapting the tool to their own research needs. Taken together, these objective and subjective measures provide evidence that the MATLAB toolbox is both user-friendly and flexible, thereby supporting the study's hypothesis regarding engagement and acceptability.

To facilitate participant interaction with the system, the 20-item Social Anxiety Questionnaire was provided as a PDF file that included all items and response options. Participants completed the questionnaire by entering their responses directly into the corresponding input fields of the GUI application, as shown in Figure 5. This design ensured that the assessment process was clear, structured, and user-friendly, while also allowing for straightforward integration of responses into the machine learning models for immediate analysis.

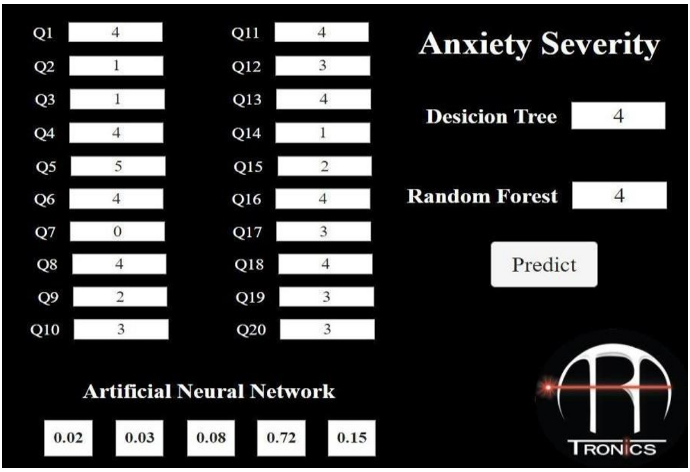


Fig 5. GUI-Based for social anxiety assessment utilized by machine learning algorithm.

One of the key advantages of using artificial neural networks (ANNs) is their ability to output normalized probability distributions across all classification categories. This feature provides valuable insight into the relative likelihood of each class and highlights potential interconnections or overlaps between them. As illustrated in the figure above, the ANN predicts that the user exhibits severe social anxiety with a probability of 72%, while also assigning a 15% probability to the "very severe" category. This probabilistic output offers a more nuanced interpretation of the user's condition, suggesting that their anxiety level lies on a spectrum influenced by adjacent classes. Such gradation is not typically provided by traditional classifiers like decision trees or random forests, which generate discrete class labels without reflecting the uncertainty or proximity between classes [13].

4 Conclusion

This study presented the design and evaluation of a GUI-based tool for social anxiety assessment using machine learning models, applied to a dataset of 500 Jordanian participants. By integrating structured self-report data with supervised classification algorithms, the system demonstrated that AI-driven methods can reliably identify and classify social anxiety severity. Random Forest achieved the highest performance, reaching perfect accuracy in both validation and testing, while Decision Trees and Artificial Neural Networks also performed strongly but with slightly lower accuracy levels. The robustness of these results confirms that self-reported questionnaire data can serve as a dependable basis for automated screening, and the strong internal consistency observed in the instrument further supports its reliability. In addition, the implementation of the models within an interactive MATLAB-based GUI provided a clear and accessible platform that allowed users to input their responses, test different algorithms, and immediately view results. Preliminary feedback indicated that the interface was easy to navigate and flexible, suggesting that such tools can help individuals—particularly those reluctant to engage with human therapists—participate in early selfassessment. Together, these outcomes provide empirical support for the use of AI-driven, user-friendly applications to enhance accessibility, precision, and personalization in mental health care.

5 Implication

This study highlights the potential of integrating machine learning models with user-friendly graphical interfaces to enhance early detection and classification of social anxiety. The findings suggest that AI-driven tools can complement traditional assessments, offering accessible and nonjudgmental platforms for individuals reluctant to seek face-to-face support. Future research should explore larger and more diverse populations, cross-cultural validation, and integration with clinical workflows. Additionally, policymakers may consider supporting the development of such tools as part of broader mental health initiatives aimed at increasing accessibility and reducing stigma.

This addresses a critical barrier for individuals with social anxiety disorder, who often avoid traditional evaluation due to fear of judgment or stigma. While the results are promising, they should be interpreted within the context of certain limitations. The dataset was geographically and culturally specific, which may influence the generalizability of the models to other populations. Future research should therefore expand data collection across diverse demographics and explore the integration of multimodal inputs, such as physiological or behavioral data, to enhance prediction robustness. Additionally, longitudinal studies would help evaluate the stability of the tool's predictions over time. In conclusion, this work demonstrates the feasibility and effectiveness of machine learning–powered, GUI-based systems for social anxiety assessment. By combining high classification accuracy with user-centered digital design, the proposed tool offers a step toward more accessible, non- intrusive, and personalized mental health support. It represents an important foundation for future AI-assisted platforms that can bridge the gap between clinical need and available psychological care.

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References

1. A. B. Isbășoiu, The Effectiveness of a Cognitive-Behavioral Therapeutic Program Delivered Online in Reducing Social Anxiety Symptoms, Bulletin of the Transilvania University of Brașov, Series VII: Social Sciences and Law **15**, 119 (2022) https://doi.org/10.31926/but.ssl.2022.15.64.2.1

2. E. Leigh and D. M. Clark, Online social anxiety cognitive therapy for adolescents (OSCA): Protocol for a randomised controlled trial, Trials **20**, 574 (2019) https://doi.org/10.1186/s13063-019-3651-6
3. J. Powell, V. Williams, H. Atherton, K. Bennett, Y. Yang, M. Davoudianfar, A. Hellsing, A. Martin, J. Mollison, and M. Shanyinde, Effectiveness and cost-effectiveness of a self-guided internet intervention for social anxiety symptoms in a general population sample: randomized controlled trial, Journal of Medical Internet Research **22**, e16804 (2020) https://doi.org/https:/doi.org/10.2196/16804
4. B. O'Bree, C. C. Walton, S. Bendall, M. Wilson, L. Valentine, C. McEnery, S. D'Alfonso, M. Alvarez-Jimenez, and S. Rice, Perceived helpfulness of a moderated online social therapy network for young people experiencing social anxiety, International Journal of Environmental Research and Public Health **18**, 2796 (2021) https://doi.org/https//doi/org/10.3390/ijerph18062796
5. Y. Chen, Exploring the impact of ChatGPT on Chinese students' foreign language anxiety in Macau's EMI higher education, Journal of Education, Humanities and Social Sciences **39**, 346 (2024)
6. G. Manoharan, L. M. Pant, R. Tewari, S. Vichare, P. Sarkar, and J. A. Dhanraj, *AI-Powered Chatbots for Mental Health Support*, in Vol. 7 (IEEE, 2024), pp. 436–440 https://doi.org/10.1109/IC3I61595.2024.10829185
7. Y. Wang, Y. Wang, K. Crace, and Y. Zhang, *Understanding Attitudes and Trust of Generative AI Chatbots for Social Anxiety Support*, in (2025), pp. 1–21
8. M. W. Ramadan, M. K. Al-Herbawi, and A. R. Ali, *Utilizing Machine Learning for Automated Depression Severity Classification: A Comparative Study of Standard Assessment Tools*, in (IEEE, 2025), pp. 1–6 https://doi.org/10.1109/ICCIAA65327.2025.11013577
9. T. Horigome, S. Yoshida, T. Tanikawa, M. Mimura, and T. Kishimoto, Modification of the therapist's facial expressions using virtual reality technology during the treatment of social anxiety disorder: a case series, Frontiers in Psychology **14**, 1030050 (2023) https://doi.org/10.3389/fpsyg.2023.1030050
10. D. Mian, Exploring the Role of AI-Powered Chatbots for Teens and Young Adults with ASD or Social Anxiety, arXiv Preprint arXiv:2412.03740 (2024)
11. M. Sakai, N. Yoshinaga, G. R. Thew, and D. M. Clark, Successful remote treatment of a client with Hikikomori using internet-delivered cognitive therapy for social anxiety disorder: a case report, Frontiers in Psychiatry **15**, 1368722 (2024)
12. T. Mitchell and M. Hill, *Machine Learning* (1997)
13. A. R. Ali, M. W. Ramadan, and P. Zometa, Machine learning for EMG-based gesture recognition in brain–computer interfaces and humanoid robots: AR Ali et al., International Journal of Intelligent Robotics and Applications 1 (2025)