2024 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER) | 979-8-3503-5059-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/DISCOVER62353.2024.10750623

Classification of Social Anxiety Disorder using Explainable Machine Learning and Pearson's Correlation Technique

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***Abstract*— Social Anxiety Disorder (SAD) is a widespread mental health issue marked by significant fear or discomfort during social interactions. It can greatly affect a person's life and overall happiness, causing problems like emotional distress, low self-esteem and depression. Thorough examination by a mental health expert is often required to diagnose SAD. The diagnostic and statistical manual of mental disorders' particular criteria are used to diagnose SAD that includes clinical interviews, self-report questionnaires, and a thorough evaluation of the individual's symptoms like severe anxiety while engaging or conversing with strangers. In this work, we employ explainable artificial intelligence (XAI) and machine learning techniques to identify SAD in individuals. Critical attributes were identified using Pearson's correlation technique. Random Forest yields optimal outcomes with 88% accuracy, 93% precision, 83% recall, 84% F1-score, and 94% Area Under Curve (AUC). Furthermore, XAI methods such as Shapley Additive Values (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) have been applied to improve the models' accuracy, comprehensibility, and precision. Automated SAD diagnosis helps in early detection and increased accessibility that allows for timely intervention, treatment, and facilites access to social anxiety testing and screening for an individual.**

***Keywords*— Machine Learning, Explainable AI (XAI), Social Anxiety Disorder, Pearson's correlation**

I. INTRODUCTION

Social Anxiety Disorder (SAD) is often known as social phobia. According to the World Health Organization (WHO), mental disorders are a broad category of issues and symptoms that usually involve a combination of odd feelings, thoughts, behaviours, and social interactions. These disorders are linked to an apparent incapacity to adjust to social conditions [1]. It can affect individuals of all ages, genders and backgrounds. People suffering from SAD are extremely selfconscious and terrified of being assessed or humiliated in public. It affects around one out of every eight people, with a lifetime prevalence of approximately 12.1%[2]. In developing nations, there is a significant rise in mental illnesses. According to reports, nearly 50% of patients who are sent to primary care clinics have some sort of mental health issue [3]. Diagnosing social anxiety disorder requires a comprehensive evaluation by medical professionals, which can be a complex process. It starts with a physical assessment to rule out any illnesses or prescription drugs that might be affecting the person's anxiety symptoms. A thorough talk is then had to learn more about the type and frequency of the individual's anxiety as well as the particular social situations that set it trigger. To identify the particular situations that cause anxiety in the individual, an evaluation of numerous social events is also conducted. Healthcare professionals frequently use self report questionnaires in addition to these examinations to systematically evaluate and quantify the patient's social anxiety symptoms. Crucially, the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM5) offers precise parameters for the diagnosis of social anxiety disorder.

Treating social anxiety disorder typically involves seeking help from a physician or a psychotherapist. However, there are also self-help strategies like learning stress reduction skills, getting enough sleep, and avoiding or limiting caffeine. Symptoms of SAD are categorized into two types, i.e., emotional and physical. Emotional symptoms consist of intense anxiety when interacting with unfamiliar individuals, avoiding situations where you might be the center of attention, and feeling afraid of situations where you could face negative judgment. Physical symptoms include rapid heart rate, sweating, dizziness, and muscle tension.

II. EXISTING LITERATURE

Li et al.[6] employed a random forest algorithm in machine learning to determine if an individual has social anxiety disorder. They have considered one of the reasons for SAD in children, i.e., parents socioeconomic attributes. Bivariate correlation analysis, logistic regression, and the random forest technique are used to create a predictive model that connected parents' socioeconomic characteristics and social anxiety disorder (SAD) based on information gathered from a questionnaire given to children and their parents in an early education setting. The outcome indicates the accuracy stands at 80.5%. The model can be used to anticipate and screen preschoolers' impulses for social anxiety, and it gives instructors a guide to providing individualized therapy.

Nova et al.[7] using text data from social media, showed how well machine learning models classified mental illnesses. Categorization of mental diseases using text data taken from mental health-related Reddit subreddits. 10,000 text entries total from four distinct subreddits—"BPD", "bipolar", "depression", and "anxiety" as well as a single category named "others" that includes "mental illness" and "schizophrenia" are included in the dataset. For the classification task, three machine learning models—LightGBM, Multi-layer Perceptron, and Multinomial Naive Bayes were employed. The post titles and the text content were used for separate training and evaluation of the models. Notably , the LightGBM model outperformed the others, with an accuracy of 0.77 for classification using text content and an even higher accuracy of 0.77 when using titles.

Shaurya et al.[8] purpose of the study, was to determine the level of anxiety and its consequences among university students in India. A questionnaire administered to engineering students at universities was used to construct the dataset, which complied with the Likert scale measurement standards. Several statistical tests were conducted on the dataset to assess its validity and reliability. Machine learning algorithms are utilized to categorize the anxiety level depending on its implications after they have been trained on preexisting data points. The Cronbach's alpha score and Pearson's correlation coefficient for the entire dataset were 0.723 and 0.823, respectively. The decision trees, random forest , support vector machines, and naive bayes algorithms have accuracy rates of 71.09%, 71.05%, 75.5%, and 71.05%, respectively.

Ganie et al.[9] three datasets were utilized: the first contained seven classes (anxiety, depression, mental health, bipolar disorder, BPD and schizophrenia), the second, which had two classes (positive and negative), and the third, which had two classes (suicide and non-suicide). There were 14 classes in the final dataset, 7 of which were in the suicidal group and 7 of which were in the non-suicidal subset.For classification and prediction, SVM, multinomial naive bayes, and logistic regression have all been utilized. The effectiveness of their models was assessed using receiver operating characteristic (ROC) curves and confusion matrices. With an accuracy of 80%, the logistic regression model outperformed the other models. Their algorithms, which provide an intuitive interface, have been employed with streamlit to predict mental health status and suicidal risk.

Vasha et al.[10] study was to identify sad individuals from their social media postings, SMS, and comments. gathered information from YouTube comments, Facebook postings, and remarks in excess of 10,000 pieces. The application of data mining and machine learning (ML) techniques made it possible to quickly identify an individual's emotions. Six classifiers were used to predict depression and nondepression, and a support vector machine (SVM) yielded the best results.

Jickson et al.[11] used machine learning approaches to look for depression symptoms in unstructured social media posts. People can identify signs of depression early on by employing advanced deep learning algorithms, like as transformers, to classify social media posts.

III. MATERIALS AND METHODS

A. Dataset

Fathi et al[12]. provided the dataset that was acquired for this study on 9th March 2020 . Dataset falls into three categories—demographic, emotional, and physical symptoms and includes 31 attributes containing both categorical and numerical data. It also contains missing values . Details of 214 individuals have been included in the data out of which 103 individuals have SAD . The term "hasSAD" describes a person's actual diagnosis of social anxiety disorder

B. Preprocessing of Dataset

Data preprocessing is essential in order to ensure that the data is in a format that is appropriate for training machine learning models, enhance model performance, and facilitate the extraction of valuable insights from the data.

Here, missing values are handled through imputation by replacing missing values with the median of the attributes. In the dataset used for the study, only one attribute, i.e., LSAS, has 54 missing values, and these values are replaced with the median of the attribute. Attributes like Id and Spin are dropped since they are not providing information for the classification. Attribute "hasSAD" is the class label in the dataset. In order to prevent biases in machine learning classifiers that could presume higher numerical values are more meaningful, the categorical data was encoded using the one-hot encoding technique[13]. Each category of the categorical variable was represented by a new variable in the encoding, with binary values (0 or 1) assigned to each class. After encoding, training and testing sets were created from the data in an 80:20 ratio.

When the attributes have similar values, the classifiers make better predictions. But if there's a big difference in values between attributes, the performance drops a lot. Also, the models tend to give more weight to attributes with larger values, regardless of their units. So, it's important to scale the data. The two approaches to do this are standardization and normalization. All of the data are kept close together via normalization, which causes them to fall between zero and one. One common method of normalization is min-max scaling which was used in this research.

Many medical datasets often have imbalanced data, where there is an imbalance in the numbers of the several classes. An imbalance can occur at three different levels: slight, moderate, and major. There is minor imbalance in the dataset used in this study. Because classifiers tend to favour the majority class, data imbalance is problematic. There are two main ways to deal with this issue: under sampling and oversampling. While oversampling adds additional information to the minority class, undersampling reduces the size of the majority class. Oversampling is usually preferred because it doesn't lose data. One effective oversampling technique is called Synthetic Minority Oversampling Technique(SMOTE), which is better than traditional methods because it doesn't just replicate existing data, reducing the risk of overfitting. Instead, SMOTE generates artificial data points using the K Nearest Neighbor (KNN) method. From the minority instances between neighbours, it selects values at random until the ratios of the two classes are equal. SMOTE, however, may result in a "line bridge" issue if instances of the minority class are also present in the majority class. To tackle this problem, an SMOTE variant called borderline SMOTE resamples observations that are near to both classes. This study uses a borderline technique to oversample the minority class in the training dataset.

C. Feature Selection

A crucial stage in machine learning is feature selection. It helps improve model performance, reduces complexity, and facilitates better decision-making. The feature selection technique employed in this study is Pearson's Correlation. The Pearson correlation coefficient is a statistical measure of the degree of a linear relationship among two random variables, typically expressed as real-valued vectors [14].

Being the first explicit measure of correlation and the most often used metric for this purpose, it is notable historically. This linear correlation coefficient, which indicates the strength of the linear association between two normally distributed variables, is explained as follows.

Correlation essentially measures the association involving variations in one variable and variations in another. Positive and negative correlation are the two forms of correlation that are most commonly seen[15]. A positive correlation exists between two variables when they move in the same direction. This suggests that a variable tends to rise in line with another, and vice versa. In the dataset used to investigate the relationship between DEF and hasSAD, for example, a positive correlation would imply that hasSAD increases in line with DEF increases. Positive correlation is typically expressed using a correlation coefficient, which has a range of 0 to 1. A value of 1 indicates perfect positive correlation.

Conversely, when two variables move against each other, negative correlation results. In this case, one variable tends to decrease when the other grows, and vice versa. In the dataset examining the association between age and having SAD, for example, a negative correlation would suggest that the likelihood of having SAD reduces with age. A correlation coefficient, which ranges from -1 to 0, is commonly used to signify negative correlation; a value of -1 denotes perfect negative correlation.

When the correlation coefficient is near either -1 or 1, there is a significant correlation [16]. A correlation value of 1 denotes a full positive correlation, or one in which both variables reach linearly as one does. A correlation coefficient of -1 indicates a perfect negative correlation, or one in which the two variables decrease linearly as one grows. The correlation between the variables is quite consistent and predictable in both situations. When the correlation coefficient is around zero, there is a weak correlation. If the correlation coefficient is closer to zero, there could not be much of a linear relationship between the variables. Changes in one variable are not highly correlated with changes in the other, according to the weak correlation coefficient.

Variables with weak correlations provide less useful information for predictive modeling. But it's important to remember that poor correlations don't always indicate insignificance. Sometimes, even weakly correlated variables can contribute valuable information when combined with other features or in specific contexts. Pearson's correlation heatmap is depicted in Figure 1.

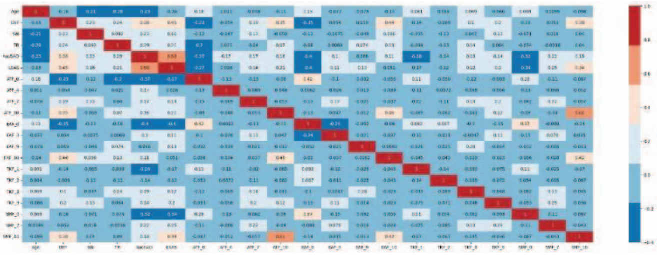

Fig. 1. Pearson's correlation

From fig1 we can observe that attributes DEF, SW, TR, LSAS, ATF 4, ATF 7, ATF 10, EAF 3, EAF 9, EAF 10 , TKF 8 ,TKF 9 ,SMF 7 , SMF 10 are positively co-related with the coefficients 0.38, 0.23, 0.29, 0.17 , 0.17, 0.16, 0.1,0.066, 0.11, 0.19, 0.14, 0.22, 0.18 respectively. Conversely, attributes Age, ATF _ 0, EAF 0 , TKF 1 , SMF 0 are negatively co-related with the co-efficients -0.23 , -0.37 , 0.4, -0.28 , -0.32 respectively .

IV. RESULTS

A. Model Evaluation

The results obtained by the classifiers are depicted in Table1. The stack is the ensemble of the five baseline classifiers.

Table I. Results obtained by various classifiers in classifying SAD.

Algorithm	Precision	Accuracy	Recall	AUC	F1Score
RF	86	86	86	86	95
LR	84	84	84	84	94
Catboost	84	86	84	84	94
Lightgbm	81	83	81	81	93
Xgboost	84	84	84	84	93
Stack	84	84	84	84	93

In the table above, the results of classic machine learning algorithms , ensembling techniques and boosting algorithms are depicted. Initially, classic algorithms like KNN , Random Forest and Logistic Regression were employed, among which Random Forest achieved superior results in precision , accuracy, recall, AUC, f1-score and hamming loss with values of 86 ,84, 86, 95,86 and 0.139 respectively. Subsequently, ensembling of Random Forest, Logistic Regression, and KNN, referred to as Stack1, was executed to enhance performance. However, this approach yielded lower accuracy compared to the individual Random Forest algorithm. Furthermore, boosting algorithms such as Catboost , Adaboost, XGBoost and LightGBM were incorporated. Notably, Catboost and XGBoost exhibited comparable results to Random Forest, with precision, accuracy, recall,precision, AUC ,f1-score and hamming loss for Catboost at 84 , 84, 86 , 94 , 84, and 0.162 respectively, and for XGBoost at 84, 84, 84, 84, 93, and 0.162 respectively.

CONFUSION MATRIX: A key technique for assessing how well categorization models work is a confusion matrix. It offers a thorough analysis of the actual classes in the dataset as well as the predictions made by the model. The matrix is organized as a table where, rows represent the actual classes and columns indicate the expected classes . The confusion matrix for Random forest algorithms is depicted in Figure 2.

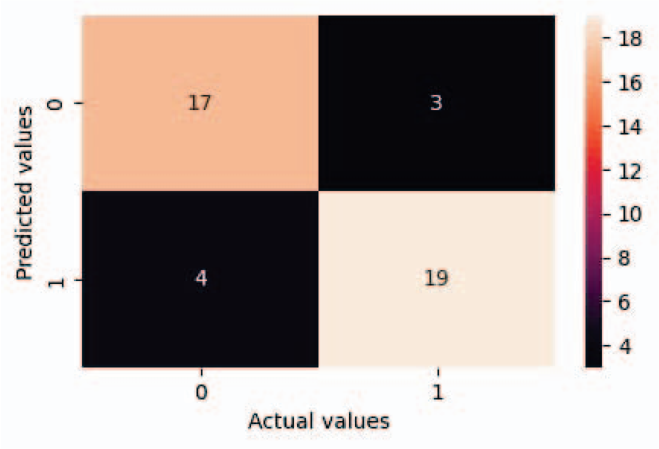

Fig. 2 . Confusion matrix of Random forest

XAI – Explainable Artificial Intelligence Machine learning has become really good at solving real world problems, sometimes even better than human beings . But often, the best results come from really complicated models that are hard for even experts to understand. These models' inner workings are hidden and hard to figure out, gaining them the name "black box" models. This lack of openness is a serious issue, especially in vital industries like healthcare. Trust is essential when it comes to acting on predictions or deciding whether to adopt a new model Explainable artificial intelligence (XAI) is vital in this situation. XAI helps people understand and trust the outcomes and results that machine learning models generate by providing explanations for their decisions[17]. In this study, XAI approaches such as Shapley additive values (SHAP) and local interpretable model agnostic explanations (LIME) are employed.

SHAP The SHAP (SHapley Additive exPlanations) technique operates by assigning credit to each feature's contribution in a model's prediction, considering all possible feature combinations[18,19]. It makes use of Shapley values and other game theory concepts to divide credit among features fairly. By exhaustively evaluating feature permutations, SHAP provides insights into how each feature impacts individual predictions, enhancing model interpretability without reliance on simplified surrogate models[19]. SHAP beeswarm plot is depicted in Figure 3.

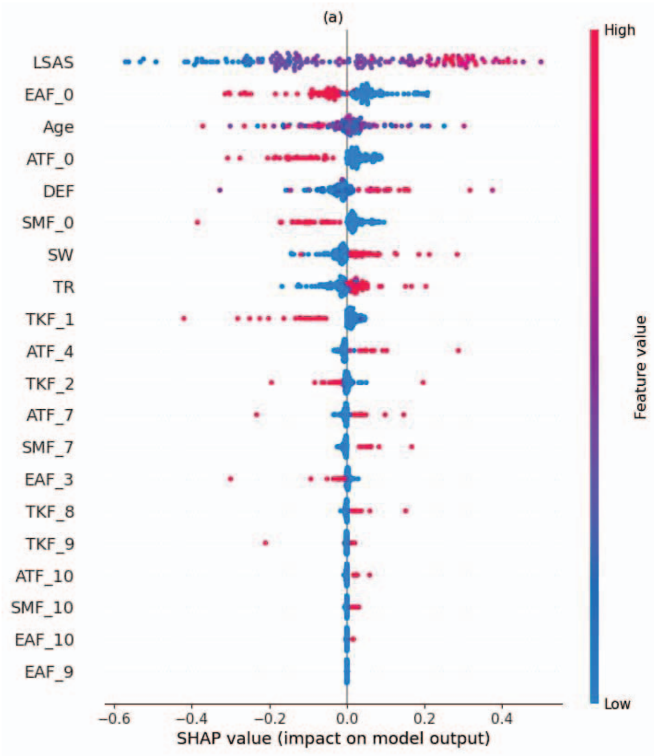

Fig. 3. SHAP value(impact on model output)

Beeswarm plot and mean graph plot of SHAP technique are depicted above . In beeswarm plot vertical line at 0.0 separates the binary classes , left of the vertical line is negative class (individual without SAD) and the right is positive class(individual with SAD). Blue and red colour in the plot indiacate lower and higher values . features in plot are arranged in descending order . According to SHAP, LSAS is the most important feature. Individual having LSAS have high chances of experiencing SAD ,and next important feature is EAF , individual with low EAF is more likely to experience SAD . and the other important features are Age , ATF , DEF , SMF , SW . Fig(b) represents the average impact of SHAP values it is the easy way to interpret . The graph indicates that the most significant characteristic with the largest mean magnitude is LSAS.

LIME operates on the principle of providing locally faithful explanations for individual predictions made by black-box models. It recognizes that while complex models may lack global interpretability, they often behave predictably in local regions of the input space[20]. By approaching the decision boundaries of the black-box model close to particular occurrences of interest, LIME aims to take advantage of this tendency.

The methodology of LIME involves generating perturbed samples around a given instance and observing the corresponding outputs from the black-box model. These perturbed samples, along with their predicted outcomes, are then then utilized to train an interpretable substitute model, like decision trees or linear regression[21]. The substitute model aims to replicate the behavior of the black-box model within the immediate vicinity of the case under study. LIME interpretations are made in Figure 4.

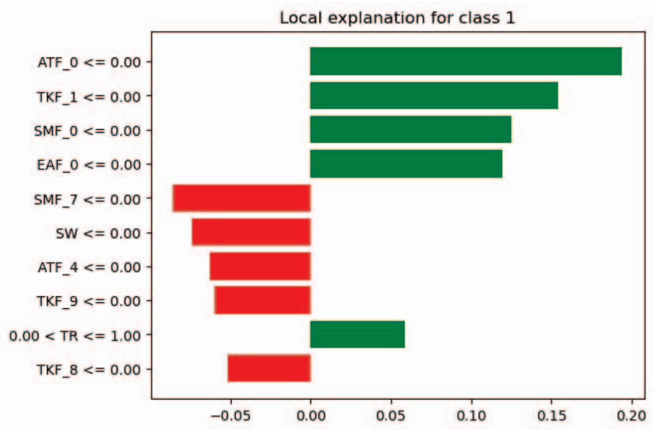

Fig. 4. Local Explanation for SAD

The diagram above illustrates the interpretability using the LIME technique. On the right side of 0.00, representing the positive class indicating “having SAD,” and on the left side, it represents the negative class. The bar’s length reveals the attribute’s significance. Thus, ATF 0 has the highest magnitude, contributing significantly to the positive class, while TR has the least magnitude, contributing less to the positive class. Conversely, for the negative class, SMF 7 has the highest magnitude, while TKF 8 has the least magnitude

V. CONCLUSION

This study considered many parameters like Gender, Age, HasFamilyhistory etc to identify whether an individual is having Social Anxiety Disorder. This facilitates easier diagnosis for physicians. Social anxiety disorder is very common and often starts at a young age, with about half of people experiencing it by age 11 and 80% by age 20. It increases the chance of developing depression and substance abuse later on [22,23]. Our research shows that individuals aged between 11-30 are experiencing Social Anxiety Disorder. Age is important feature in the study as discussed above, it is negatively correlated with SAD. The possibility of experiencing SAD decreases with increase in age. This study has several benefits. Machine learning models can make diagnosing SAD early and simple.

Using XAI techniques helps explain the model’s results, showing which parameters contribute to SAD. These parameters can be studied further to understand their relationship with SAD. Neverthless, a limitation of this study is that it includes a small number of individuals. Ezzi et al. [24] categorized three severity categories of SAD using graph theory features and partial directed coherence (PDC). and used Support Vector Machine to get the best results, with a 92.78%accuracy rate. Kim et al. [25] used resting-state brain functional characteristics to train machine learning models ,sought to predict the level of SAD in young people. XGBoost fared better than the other machine learning models, with an even accuracy of 77.7%and an F1 score of 0.815.. Fathi et al [26] trained the ANFIS model using a preprocessed dataset including seven input features, and then optimized the process of learning across 41 epochs using a hybrid method. With the sensitivity of 97.14%, specificity of 100%, and accuracy of 98.67%, the model performed well.

Social anxiety disorder (SAD) causes strong anxiety when interacting with others, leading to fear, embarrassment, and difficulty meeting strangers. While this condition can be challenging, there are effective treatments, including therapy and medication. Typically, the DSM-5 test is used to diagnose SAD. In this study, we employed machine learning and novel methods for explaining artificial intelligence (XAI) to forecast SAD. We experimented with various machine learning models, such as a unique stack model, to distinguish individuals with SAD from those without it. XAI techniques helped us understand how the models made their predictions. Our findings demonstrate that XAI and machine learning can assist in the better diagnosis and treatment of SAD. Early detection and therapy are critical for controlling mental health.

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