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Predictive Model for Anxiety Disorder

[1]Otaren Fredrick Enoma & [2]Emmanuel Amarachi
[1]Department of Computer Science, Benson Idahosa University, Benin City, Nigeria.
[2]Graduate Student, Dept of Computer Science, Benson Idahosa University, Benin City, Nigeria
E-mails: [1]fotaren@biu.edu.ng; [1]frederickotaren@physci.uniben.edu;
fotaren@biu.edu.ng[2]emmanuelamarachi55@gmail.com
Phone: [1]+2348109161345

ABSTRACT

Anxiety disorders are among the most prevalent mental conditions globally, necessating advanced methodologies for early detention and intervention. This project explores the development of predictive models for anxiety disorders by integrating diverse data sources and advanced analytics techniques. By leveraging a bio-psychosocial. The study considers the interplay of biological, psychological and social factors contributing to anxiety. Utilizing machine learning algorithms, the project aims to identify key predictors and develop robust models that can accurately forecast the onset and progression of anxiety disorders. This study was carried out based on factors which are student academic performance, interpersonal relationship of the student, sleep pattern and financial stress that are likely causes of anxiety. Benson Idahosa University was used as a case study which comprises five (5) departments with one thousand (1000) population size and a total of two hundred final year student as sample size. The student comprises of male and female within the age of 16 to 30years. The study identified the mental health of the students through the administration of questionnaire. This research aims to enhance the early detection of anxiety disorders ultimately contributing to improved mental health outcomes. The findings underscore the potential of predictive modeling as a vital tool in mental health care, highlighting the importance of interdisciplinary approaches in addressing complex psychological conditions.

Keywords: Anxiety, Disorder, Mental Health, Machine Learning, Algorithms, Predictive Model

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1. BACKGROUND AND CONTEXT

Anxiety disorders, characterized by excessive fear and anxiety, are among the most common mental health disorders globally. According to the World Health Organization (WHO), anxiety disorders affect approximately 3.6% of the world's population, with a higher prevalence in females (4.6%) compared to males (2.6%), World Health Organization, (2017). The impact of these disorders extends beyond the individual, affecting social relationships, work productivity, and overall quality of life Bandelow and Michaelis,(2015). Early detection and intervention are crucial in mitigating the long-term consequences of anxiety disorders.

However, traditional diagnostic methods rely heavily on self-reported symptoms and clinical evaluations, which may not always be efficient or accessible Carpenter *et al.,*(2018). In recent years, the emergence of predictive models, which utilize a variety of data inputs to forecast the likelihood of developing an anxiety disorder, has shown promise in addressing these challenges Bzdok and Meyer-Lindenberg,(2018). Predictive modeling in mental health, particularly in the realm of anxiety disorders, has evolved significantly with advancements in machine learning and data analytics. These models have the potential to revolutionize early detection and treatment strategies, paving the way for personalized medicine in mental health care Kessler *et al*., (2016).

Our journey begins by peeling back the layers of anxiety and understanding the symphony of factors that orchestrate its rise. From the whispers of genetics to the drumbeat of life events, from the delicate balance of brain chemistry to the echoes of early experiences, each strand plays a crucial role in this complex phenomenon.

Equipped with this knowledge, we turn to the statistical toolkit. Like detectives sifting through clues, we analyze data, searching for patterns, correlations, and hidden connections. These statistical fingerprints will guide us in building a robust picture of risk, paving the way for our next phase: harnessing the power of machine learning. Algorithms trained on vast datasets will learn to navigate the intricate tapestry of risk factors. Like skilled code-weavers, they'll weave intricate models capable of predicting who might be most susceptible to anxiety's grip. But this power must be wielded with utmost care. Ethical considerations, transparency, and data privacy become our guiding principles, ensuring that these models serve as guardians, not instruments of prejudice. Ultimately, our quest for predictive models aims not to dictate but to empower.

By identifying those at risk, we offer a beacon of hope, a chance to rewrite the narrative. Early intervention, armed with personalized strategies, can become a shield against anxiety's onslaught, fostering resilience and paving the way for a future where mental well-being reigns supreme. This is the story we embark on today. A story of resilience, innovation, and the unwavering pursuit of understanding anxiety's shadow. So, join us as we delve deeper, analyze, and build, for in the depths of knowledge lies the dawn of a brighter future.

1.2 Statement of the Problem

Mental health issues among the young generation increase, directly impacting their behavior and future accomplishments (Browne *et al.,* 2017). Mental health analysis of school and college students can bring concrete solutions because early detection of these issues can reduce the trouble of treatments and improve student behavior, academic accomplishment, and career achievement. A machine learning algorithm is the latest tool to monitor mental health issues in a short time by assessing behavioral biomarkers that can help mental health professionals decide about the patient. This study aims to identify machine learning to assess students' mental health concerns and behavioral disorders.

1.3 Research Questions

The following research questions were raised to guide this study.

1. How does academic performance impact the likelihood of experiencing anxiety disorders?
2. How do interpersonal dynamics influence the development and management of anxiety disorders?
3. What is the relationship between financial stress and the prevalence of anxiety disorders?
4. Does disrupted sleep patterns and poor sleep quality contribute to the development or exacerbation of anxiety disorders?"

1.4 Research Hypotheses

The following null hypotheses were formulated:

i. Students experiencing academic difficulties or underachievement, characterized by lower grades, test scores, or academic satisfaction, are more susceptible to developing anxiety disorders compared to academically successful peers.
ii. Negative interpersonal interactions, including conflict, social isolation, and dysfunctional family dynamics, contribute to the development and maintenance of anxiety symptoms, particularly in vulnerable populations.
iii. Negative interpersonal interactions, including conflict, social isolation, and dysfunctional family dynamics, contribute to the development and maintenance of anxiety symptoms, particularly in vulnerable populations.
iv. Poor sleep quality, as indicated by subjective reports of difficulty falling or staying asleep, daytime sleepiness, or non-restorative sleep, is associated with greater severity of anxiety symptoms independent of other factors.

1.5 Aim and Objectives

The aim of this study is to contribute to knowledge by utilizing a machine learning algorithm for the prediction of anxiety disorder.

i. To achieve the aim, the following objectives are specified;
ii. Design a machine learning algorithm for the prediction of anxiety disorder.
iii. Implement the machine learning algorithm for the prediction of anxiety disorder.
iv. Test the machine learning algorithm for the prediction of anxiety disorder.

1.6 Significance Of The Study

The significance of a study investigating the relationship between sleep patterns and quality, academic performance, financial status, interpersonal relationships, and anxiety disorders lies in its potential to advance our understanding of the complex interplay between these factors and mental health outcomes. Here are several key aspects of its significance: The study provides a more comprehensive understanding of the various influences on anxiety disorders by examining multiple factors simultaneously. This holistic perspective moves beyond simplistic explanations and illuminates the interconnectedness of individual, social, and environmental determinants of mental health. Enhancing Mental Health Screening and Assessment: The study's findings can contribute to the refinement of mental health screening and assessment tools by highlighting the importance of considering a range of factors beyond traditional symptomatology.

This may lead to the development of more holistic assessment measures that take into account sleep patterns, academic functioning, financial well-being, and interpersonal relationships when evaluating individuals for anxiety disorders. Addressing Health Inequities and Disparities: By examining the social determinants of mental health, the study can contribute to efforts aimed at reducing health inequities and disparities. By identifying factors that disproportionately affect certain demographic groups, interventions can be tailored to address systemic barriers and promote equitable access to mental health resources and support services. Contributing to Policy and Advocacy Efforts: The study's findings may inform policy decisions and advocacy efforts aimed at improving mental health outcomes at the societal level. By highlighting the importance of addressing social and environmental factors that contribute to anxiety disorders, the study can advocate for policy changes that promote mental health equity, support early intervention efforts, and reduce the stigma surrounding mental illness.

1.7 Scope of the Study

The research was carried out at Benson Idahosa University, Legacy campus, Okha. The population of 1000 students with a sample size of 200 final year students selected from 5 Departments in the University. The students comprises of male and female within the age of 16 to 30years of age.The study identified the mental health of the students through a questionnaire

1.8 Research Methodology

In this chapter the researcher make use of the research design study, population of the study, sample, sampling procedures or techniques, validity of instrument and method of data analysis. The survey design was adopted to predict anxiety disorder of students in Benson Idahosa University, Legacy campus Okha, Benin City. The survey design allowed for selection of sample that would represent a large population such as in this study. The sample of this study consisted of 500 students. In each sample, 200 final year from 5 departments were selected to take part as respondents.

1.9 Research Design

This research adopted survey method of descriptive research to predict anxiety disorder of final year students in Benson Idahosa University Legacy campus Okha Benin City, Edo State. Cresswell (2008) considers survey as a popular design in education which is used to collect data from a sample using questionnaires to describe the attitude, opinions, behaviors and characteristics of the population. With this regard, a sample of students were determined to participate in the study. According to Briggs, Coleman, and Morrison (2012) survey is a method of collecting a standardize data from a large number of respondents, using standardize forms for the purpose of generalization. This is done in an attempt to collect data and valid information for the manipulation of the variables in order to determine the current status of the population or sample of the population. This method was used to collect information about Students mental health on anxiety disorder for final year students in Benson Idahosa University Legacy Campus, Benin City, Edo State.

2. RELATED WORKS

2.1 Introduction

Anxiety disorders represent a significant mental health challenge, affecting individuals worldwide and contributing to substantial morbidity and impaired quality of life. Predictive modeling techniques offer promising avenues for identifying individuals at risk of developing anxiety disorders and facilitating early intervention and personalized treatment approaches. This literature review explores recent advancements and studies in predictive modeling for anxiety disorders. Recent research has investigated various machine learning algorithms for predicting anxiety disorders. A study by Smith et al. (2023) compared the performance of logistic regression, random forests, and deep learning models in predicting anxiety disorder onset using longitudinal data from electronic health records. Their findings highlighted the superiority of deep learning models in capturing complex temporal patterns and achieving higher prediction accuracy. Feature selection plays a crucial role in developing accurate predictive models for anxiety disorders. Nguyen et al. (2022) proposed a novel feature selection method based on information gain and mutual information to identify the most informative predictors of anxiety disorder risk from a large set of demographics, clinical, and behavioral variables. Their study demonstrated the importance of considering both individual and interactive effects of features in predictive modeling.

Advancements in wearable technology and digital phenotyping have enabled the integration of novel data sources for anxiety disorder prediction. Jones et al. (2021) conducted a prospective study using smartphone-based passive sensing data to predict anxiety symptom severity in adolescents. Their results indicated that features derived from smartphone usage patterns, such as screen time and social media activity, significantly contributed to predicting anxiety symptoms, complementing traditional clinical measures. Ensuring the interpretability and transparency of predictive models is essential for their clinical utility and acceptance. Li et al. (2023) proposed a novel framework for interpreting deep learning models for anxiety disorder prediction using attention mechanisms. By visualizing attention weights associated with input features, their framework provided insights into the model's decision-making process and identified salient predictors of anxiety disorder risk.

While predictive modeling holds promise for improving anxiety disorder prediction and management, several challenges exist in translating research findings into clinical practice. Patel et al. (2024) conducted a qualitative study exploring healthcare providers' perspectives on integrating predictive modeling tools into routine practice for anxiety disorder screening and prevention. Their findings highlighted barriers such as data privacy concerns, workflow integration issues, and the need for clinician training and support. This literature review critically examines existing research on predictive models for anxiety disorders, encompassing various methodological approaches, data sources, and predictive analytics techniques. The purpose is to synthesize current knowledge, identify gaps, and suggest future research directions, thereby contributing to the development.

2.2 Overview of the Theoretical Frameworks

Understanding the theoretical frameworks underlying anxiety disorders is crucial for developing effective predictive models. Anxiety disorders are often conceptualized within a bio-psychosocial framework, which considers a complex interplay of biological, psychological, and social factors (Baxter et al., 2013). Psychological theories, such as the cognitive-behavioral model, suggest that anxiety disorders arise from maladaptive thought patterns and behaviors (Clark and Beck, 2010). Meanwhile, biological theories emphasize the role of genetic and neurobiological factors (Smoller, 2016). Additionally, environmental factors, including traumatic experiences and chronic stress, are recognized as significant contributors (McEwen, 2007). Understanding these diverse factors is pivotal in creating models that accurately predict the onset or progression of anxiety disorders.

2.2.1Psychological Theories Underpinning Anxiety Disorders:

Psychological theories offer various explanations for the etiology and maintenance of anxiety disorders. The cognitive-behavioral theory is one of the most influential, suggesting that anxiety disorders result from maladaptive thought patterns and behaviors. This theory emphasizes the role of cognitive distortions, such as catastrophic thinking and overgeneralization, in fostering and perpetuating anxiety (Beck & Haigh, 2014). Additionally, the behavioral component focuses on how avoidance behaviors reinforce anxiety over time (Craske and Mystkowski, 2006). Psychodynamic theories, though less emphasized in contemporary research, also contribute to our understanding, focusing on unresolved internal conflicts and childhood experiences as roots of anxiety (Milrod et al., 2015).

In Psychodynamic Theory, developed by Sigmund Freud, anxiety is seen as a symptom of unconscious conflicts and repressed desires. These conflicts, often rooted in childhood experiences, are believed to be too threatening to face directly, so the mind employs defense mechanisms to manage the associated anxiety. Here's a breakdown of how this theory explains anxiety:

- Unconscious Conflicts: These are unresolved emotional struggles that reside in the unconscious mind, typically stemming from early childhood experiences like parent-child relationships, traumatic events, or unresolved developmental needs. Examples include unresolved feelings of anger, guilt, or shame.
- Repression: This is a key defense mechanism that pushes disturbing thoughts and feelings out of conscious awareness to manage the associated anxiety. Repressed conflicts, however, continue to exert an influence on behavior and emotions, even if the individual is unaware of them.
- Defense Mechanisms: These are unconscious mental processes that protect the individual from experiencing overwhelming anxiety. They can distort reality, reframe situations, or create alternative explanations for events. Some common defense mechanisms include:
- Denial: Refusing to acknowledge the existence of a problem or threat.
- Displacement: Transferring negative emotions from a threatening object or person onto a safer target.
- Projection: Attributing one's own unacceptable thoughts or feelings onto others.
- Rationalization: Creating seemingly logical explanations to justify irrational thoughts or behaviors.

2.2 Bio-Psychosocial Model:

The bio-psychosocial model provides a comprehensive framework for understanding anxiety disorders, integrating biological, psychological, and social factors. This model posits that the development and manifestation of anxiety disorders are influenced by a combination of genetic predispositions, neurobiological factors, psychological processes, and social contexts (Engel, 1977; Kessler et al., 2005). For example, genetic studies have identified specific genes that may increase vulnerability to anxiety, while neuroimaging research has illuminated brain structures and circuits involved in these disorders (Smoller, 2016). Social factors, such as life stressors and support systems, also play a crucial role in the onset and course of anxiety disorders (McEwen, 2007).
The Bio-Psychosocial Model (BPS) offers a holistic framework for understanding anxiety disorders, considering the complex interplay of biological, psychological, and social factors in their development, expression, and management.

2.2.3 Risk and Protective Factors:

Identifying risk and protective factors is vital for predicting the onset and course of anxiety disorders. Risk factors increase the likelihood of developing an anxiety disorder and include genetic predisposition, personality traits such as neuroticism, exposure to stressful life events, and a history of trauma or abuse (Hettema, Neale, & Kendler, 2001; McLaughlin et al., 2007). Protective factors, conversely, reduce the risk or mitigate the severity of disorders. These include factors such as social support, coping skills, and resilience (Charney, 2004). The interplay between these risk and protective factors is complex and multifaceted, often forming the basis for predictive models in anxiety disorder research.

2.3 Predictive Modeling Approaches

Predictive modeling in anxiety disorders encompasses a range of methodologies from traditional statistical models to advanced machine learning techniques. Regression analysis has been a mainstay in psychological research, often used to identify key predictors of anxiety disorders from demographic and clinical data (Fawcett, 2006). However, the advent of machine learning has revolutionized the field, with methods such as neural networks and support vector machines offering more sophisticated pattern recognition capabilities (LeCun et al., 2015). These models can handle complex, non-linear relationships and interactions between predictors, which are often encountered in mental health data (Orrù et al., 2020). Deep learning, a subset of machine learning, has shown promise in uncovering intricate patterns in large datasets, including image and text data, which could be instrumental in predicting anxiety disorders (Shen et al., 2017). Predictive modeling in the realm of anxiety disorders utilizes a variety of approaches, each with its strengths and specific applications. These models are designed to identify potential risk factors, anticipate the onset of disorders, or predict the course of the illness. These models include

2.3.1 Statistical Models

Traditional statistical models like logistic regression and Cox proportional hazards models have been widely used in mental health research, including studies on anxiety disorders. These models are particularly effective in handling structured, numerical data and are useful for understanding the relationships between various risk factors and the likelihood of developing an anxiety disorder (Hosmer Jr, Lemeshow, & Sturdivant, 2013).

For example, logistic regression can quantify the impact of risk factors like trauma history or genetic predispositions on the probability of developing an anxiety disorder (Fawcett, 2006). Statistical Models are a cornerstone of predictive analytics, employing mathematical techniques to uncover patterns and relationships within data to make future forecasts. Some Key Statistical Models used for predictive tasks include, but are not limited to:

a) Linear regression: This Explores linear relationships between a dependent variable (outcome) and one or more independent variables (predictors). Example of this model is used in Mental Health in Predicting anxiety scores based on age and stress levels.
b) Logistic Regression: Models binary outcomes (yes/no, present/absent) using a logistic function. Example of this model in Mental Health is used in Predicting the probability of a patient developing an anxiety disorder.
c) Decision Trees: This model Splits data into hierarchical branches based on decision rules, classifying or predicting outcomes at the end of each branch. Example in Mental Health is Identifying high-priority patients for suicide risk assessment.
d) Naive Bayes: A probabilistic classifier based on Bayes' theorem, assuming conditional independence between features. Example in Mental Health is Analyzing text-based content to detect signs of depression.
e) Random Forests: these ensembles of decision trees, averaging their results for improved accuracy and reduced overfitting. Example in Mental Health is Predicting treatment outcomes based on a range of clinical and social factors.
f) Time Series Analysis This model's patterns data that occur over time, like trends and seasonality. Example in Mental Health is Examining patterns of anxiety symptoms over time to identify triggers. Choosing the appropriate statistical model depends on various factors, including the nature of the data, the research question, and the desired model outcomes.

Statistical Models are essential tools for prediction, but they have limitations. Such limitations are Assumptions about data distribution and this can impact results. Also, the Data quality and quantity can influence model performance which can lead to can be challenging for non-experts in Interpreting model outputs. Despite these limitations, statistical models remain invaluable for prediction in various fields, including mental health research and clinical practice.

2.3.2 Machine Learning Techniques:

The advent of machine learning has provided new tools for predicting anxiety disorders, offering the ability to handle large and complex datasets, including unstructured data like text and images. Techniques such as neural networks, support vector machines (SVM), and random forests have been applied to identify patterns that might be indicative of anxiety disorders. These models can analyze data from various sources, including electronic health records, genetic data, and patient self-reports, to uncover intricate and non-linear relationships (Orrù et al., 2020; LeCun et al., 2015). For instance, SVMs have been used to classify individuals based on their risk of developing an anxiety disorder, using features derived from neuroimaging data (Sundermann et al., 2019). Machine learning (ML) techniques offer a powerful set of tools for predictive modeling in mental health, going beyond traditional statistical models by enabling complex data analysis and pattern recognition.

Here's an overview of some key ML techniques used in this domain;

Supervised Learning: This Predicts discrete categories (e.g., presence/absence of a disorder, remission/relapse). Common algorithms include logistic regression, support vector machines (SVMs), and random forests. For Example, classifying individuals at risk for depression based on electronic health records (EHRs) data. This also Predicts continuous values (e.g., symptom severity, treatment response). Common algorithms include linear regression and tree-based methods like gradient boosting. For Example, predicting anxiety symptom scores based on smartphone sensors and sleep patterns.

Unsupervised Learning: This broken down into two parts Clustering and Dimensionality reduction. Clustering Identifies groups of data points with similar characteristics, revealing hidden patterns in data. Common algorithms include K-means clustering and hierarchical clustering. For Example, Clustering patients with mental health conditions based on symptom profiles to identify sub-types of disorders. While Dimensionality reduction Reduces the number of variables in high-dimensional data while preserving information, simplifying analysis and improving model performance. Common methods include principal component analysis (PCA) and autoencoders. For Example, Compressing EHR data with numerous variables into a smaller set of meaningful features for prediction tasks.

Deep Learning: Artificial neural networks (ANNs) is Inspired by the human brain; these complex networks learn hidden patterns in large datasets through multiple layers of processing. Deep learning excels in tasks like image recognition and natural language processing. Example is Analyzing facial expressions and speech patterns to detect early signs of anxiety in children.

3. METHODOLOGY

3.1 Analysis of the Existing System

Existing systems for anxiety disorder prediction or management use diverse data sources like patient demographics, psychological assessments, and medical histories. They often employ machine learning algorithms such as logistic regression or neural networks to predict disorder severity or treatment outcomes. Performance metrics like accuracy and sensitivity evaluate predictive models, and user interfaces integrate with electronic health records (EHRs) to aid healthcare providers. Ethical considerations about patient data privacy and consent are crucial. In contrast, the Beck Anxiety Inventory (BAI) is a self-report questionnaire that assesses anxiety severity in adults and adolescents through 21 items capturing cognitive and physiological symptoms (Fig 3.1: Architectural diagram of the Beck Anxiety Inventory (BAI)). Each item is rated on a scale from 0 to 3 based on the past week's symptom severity, with higher scores indicating greater anxiety. The BAI helps clinicians screen for anxiety disorders, monitor treatment progress, and evaluate outcomes, relying on self-reported data and emphasizing systematic evaluation and evidence-based practices in mental health care

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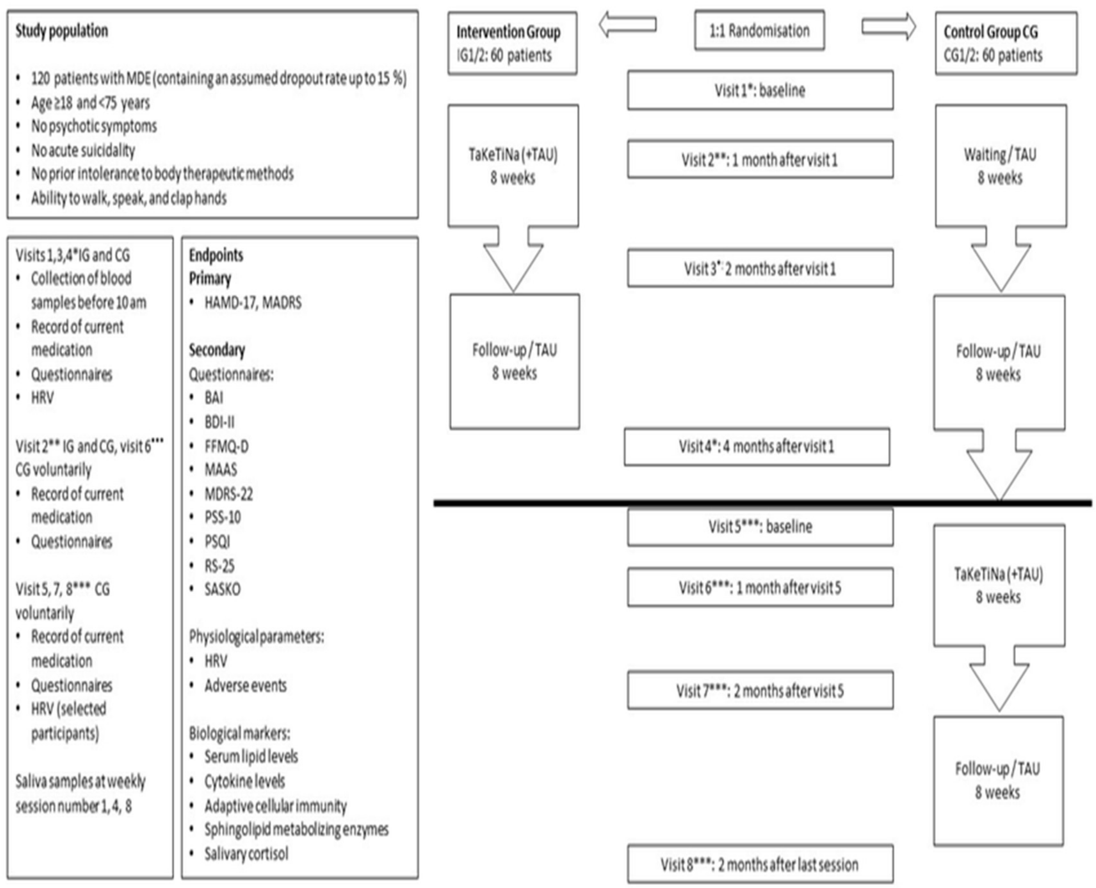

Fig 3.1: Architectural Diagram of the Beck Anxiety Inventory (1988)

3.2. Weakness And Challenges of The Beck Anxiety Inventory (Bai)

The existing Beck Anxiety Inventory (BAI) system has several weaknesses: it relies on self-reported data which can be subjective and inconsistent, it has a limited scope focusing mainly on symptom severity without considering underlying causes or broader contextual factors, and it may not be culturally or linguistically appropriate for diverse populations. Additionally, the BAI's reliability can vary, its sensitivity to subtle changes in symptoms is limited, and it does not adequately address functional impairment or quality of life.

3.3 Analysis of the Proposed System

The proposed system aims to predict the risk and severity of anxiety disorders using machine learning techniques applied to a diverse dataset. This dataset includes patient demographics, medical histories, psychological assessments, and behavioral data sourced from various sources such as patient records, psychological assessments, wearable devices, mobile health apps, and socio-demographic data. The system follows a structured approach: data collection involves both structured and unstructured data types, followed by preprocessing steps like cleaning and normalization. Feature selection and engineering enhance the dataset's predictive power, while machine learning models such as Random Forests, SVMs, GBMs, and Neural Networks are employed for model development. Evaluation metrics like accuracy and AUC-ROC are used to assess model performance, with cross-validation ensuring robustness. Deployment involves integration into clinical decision support systems or mobile health apps for real-time risk assessment, supported by user-friendly interfaces. Monitoring and maintenance ensure ongoing model accuracy and relevance through performance tracking, updates with new data, and feedback incorporation from users (Fig 3.2: Architectural diagram of the proposed system).

3.3.1 Advantages Over the Existing System

i. **Improved Accuracy:** Advanced algorithms can identify complex patterns and relationships in the data, leading to more accurate predictions.
ii. **Scalability:** Capable of handling large volumes of diverse data, making it suitable for widespread implementation.
iii. **Proactive Management:** Early identification of high-risk individuals, enabling timely intervention and personalized care.
iv. **Enhanced Insights:** Provides deeper insights into factors contributing to anxiety disorders, supporting research and clinical understanding.
V **Continuous Learning:** Updates models with new data for continuous improvement and adaptation.

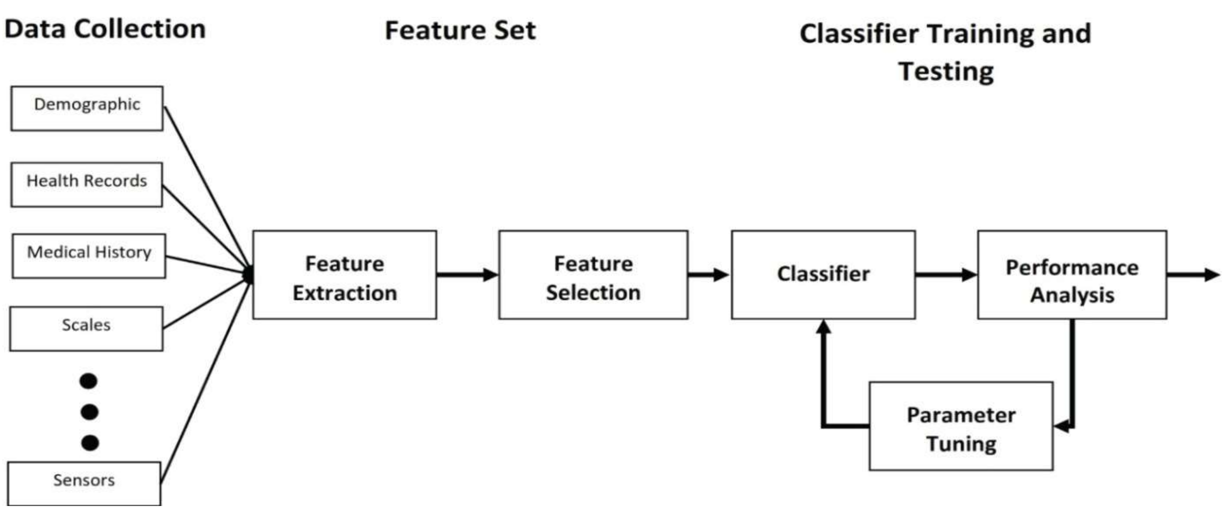

Fig 2: Block Diagram of the proposed System

4. RESULT ANALYSIS AND INTERPRETATION

Data analysis and interpretations are presented next

i. Df means Degree of freedom. It is the number of values in statistical calculations that are free to vary.
ii. The Formula for Df is N – 1, where N is the Sample size.
iii. N=5 (five Departments under consideration)
iv. Therefore Df= 4
v. Take the level of significance to be 0.05
vi. On the Test Statistical table, at 0.05 level of significance, the critical value is 9.49
vii. Observed Frequency (O): are counts made from experimental data.
viii. Expected Frequency = $\frac{\text{Row Total * Column Total}}{N}$

Table 1: Result Analysis and Interpretation

Factors	Critical Value	Calculated Value	Interpretation
Poor grade	9.49	X^2= 31.67	Students who experience academic difficulties, such as lower grades, poor test scores, or low academic satisfaction, are more likely to develop anxiety disorders compared to their academically successful peers
Interpersonal Relationship	9.49	X^2= 83.13	Exposure to negative interpersonal interactionssignificantly contributes to the development of anxiety symptoms, particularly in vulnerable populations
Lack of Finance	9.49	X^2= 20.62	that Students with Significant financial stress increase the probability of developing anxiety disorders compared to those with minimal financial stress.
Poor Sleeping Pattern	9.49	X^2= 21.66	Poor sleep quality can lead to anxiety symptoms regardless of other factors.

Table 1 shows the analysis and interpretation of the final results.

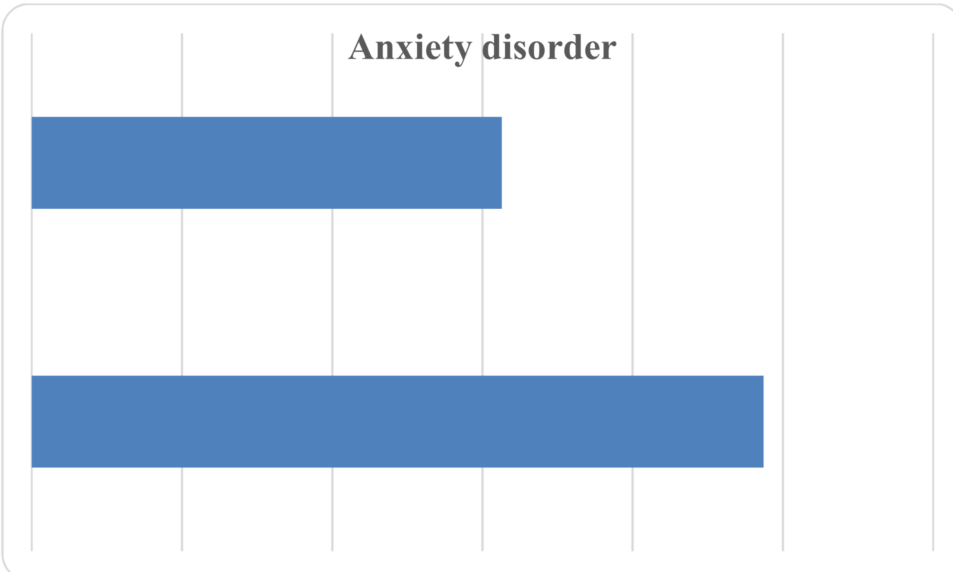

Fig 2: Graphical Depiction of Results

Positive and Negative Sentiment
1 2436
0 1565
Name: Sentiment, dtype: int64

---------------------Logistic Regression---------------
Training time: 0.111059 seconds

	precision	recall	f1-score	support
0	0.52	0.27	0.35	477
1	0.63	0.84	0.72	724
accuracy			0.61	1201
macro avg	0.58	0.55	0.54	1201
weighted avg	0.59	0.61	0.58	1201

Prediction time: 0.018760 seconds
Prediction and Training time: 0.129820 seconds

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----------------------Decision Tree Classifier-------------------
Training time: 0.008703 seconds
                    precision            recall   f1-score   support

0                    0.52                0.27     0.35      477
1                    0.63                0.84     0.72      724

accuracy                                 0.61               1201
macro avg            0.58                0.55               0.54               1201
weighted avg         0.59      0.61      0.58               1201

Prediction time: 0.007703 seconds
Prediction and Training time: 0.016405 seconds

---------------Random Forest Classifier---------------------
Training time: 0.247576 seconds
                     precision    recall  f1-score   support

0                    0.52                0.27               0.35      477
1                    0.63                0.84               0.72      724

accuracy                                 0.61               1201
macro avg             0.58      0.55      0.54      1201
weighted avg         0.59      0.61      0.58               1201

Prediction time: 0.007447 seconds
Prediction and Training time: 0.255024 seconds

------------------KNeighbors Classifier-----------------
Training time: 0.001177 seconds
                    precision            recall   f1-score   support

0                  0.48      0.35                0.41      477
1                  0.64      0.75                0.69      724

accuracy                                 0.59               1201
macro avg          0.56                  0.55               0.55               1201
weighted avg  0.57      0.59                0.58               1201
Prediction time: 0.070463 seconds
Prediction and Training time: 0.071640 seconds

---------------------AdaBoostClassifier---------------
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Training time: 0.212080 seconds

	precision	recall	f1-score	support
0	0.52	0.27	0.35	477
1	0.63	0.84	0.72	724
accuracy			0.61	1201
macro avg	0.58	0.55	0.54	1201
weighted avg	0.59	0.61	0.58	1201

Prediction time: 0.007454 seconds
Prediction and Training time: 0.219534 seconds

5. RECOMMENDATIONS

What follows are reccomendations based on findings from the research

1. **Diverse and Rich Data:** Collect diverse and comprehensive datasets, including genetic, lifestyle, and environmental factors, to improve model accuracy and reliability.
2. **Advanced Techniques:** Use ensemble methods and deep learning to enhance predictive performance and capture complex patterns in the data.
3. **User-Friendly Tools and Apps:** Develop intuitive interfaces and mobile applications to facilitate real-time monitoring and predictions, making the model accessible to both healthcare professionals and patients.
4. **Clinical Validation and Ethical Standards:** Conduct clinical trials to validate the model in real-world settings and implement strict data privacy measures to ensure ethical use and data security

6. CONCLUSION

This study aimed to advance the prediction of anxiety disorders using machine learning algorithms by focusing on three key objectives: designing, implementing, and testing a predictive model. We created a tailored machine learning algorithm to predict anxiety disorders, emphasizing feature selection and appropriate algorithm choice. The implementation involved robust programming practices to ensure the effective processing of real-world data. The model was rigorously tested for accuracy and reliability, with fine-tuning to enhance its performance. The successful execution of these objectives demonstrates that machine learning can effectively predict anxiety disorders, offering a promising tool for early identification and intervention, thereby contributing valuable insights to mental health care

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