ANXIETY LEVEL CLASSIFICATION SYSTEM

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ABSTRACT

The research offers a solution to the challenge of early anxiety detection and classification in mental health diagnostics. The proposed strategy involves developing a ML model that classifies individuals into four distinct anxiety levels: severe, moderate, mild, and no anxiety. By inspecting multiple factors including age, gender, BMI, depression severity, and sleep patterns, the system provides automated and accurate anxiety assessment. Mental health diagnosis is often hindered by reliance on manual assessments, which can be subjective and inconsistent. A novel machine-learning-based anxiety classification system offers a solution, providing objective and data-driven insights into anxiety diagnosis. This system supports machine-learning algorithms to analyse input features, facilitating efficient and accurate assessment of anxiety levels across large populations. Overall, the proposed method presents an innovative and cost-effective alternative to traditional anxiety assessment approaches.

Keywords– Anxiety Classification, Machine-learning, Mental Health, Early Detection, Automated Assessment.

INTRODUCTION

Anxiety is one of the most common mental health challenges affecting millions of people around the world, often impacting daily life and overall well-being. As awareness of mental health issues continues to grow, the need for accurate and timely stress assessments has become more important than ever. Thanks to advancements in machine learning, we can now better understand and measure stress levels—ranging from mild and moderate to severe or no stress—by analysing factors like age, gender, body weight, stress level, and sleep patterns.

Unlike traditional psychological assessments, which often rely on academic-based metrics, machine learning offers a more objective and practical approach to identifying and analyzing stress. One of its key benefits is the ability to detect stress early, allowing doctors to provide personalized treatment based on an individual's specific needs. Machine-learning algorithms can predict stress levels with high accuracy, eliminating the need for time-consuming manual evaluations and offering quick, data-driven insights. Beyond simple classification, these systems enable continuous stress monitoring, constantly updating assessments using advanced techniques. With features like scalability, automated analytics, and real-time insights, machine learning is transforming how healthcare professionals support their patients' mental well-being. The use of machine-learning in this context is not entirely new, but it represents a significant shift away from conventional methods, allowing healthcare organizations to process large amounts of data efficiently and provide quicker, more accurate diagnoses. one of the key challenges in applying machine-learning to mental health is ensuring that sensitive health data is handled responsibly and with accuracy. The system overcomes these challenges by employing rigorous data validation and analysis techniques, ensuring that predictions are reliable and meaningful. This approach not only offers the promise of better mental health care but also paves the way for a future where automated, data-driven insights play a central role in healthcare.

METHODOLOGY

1.1 BLOCK DIAGRAM AND EXPLANATION

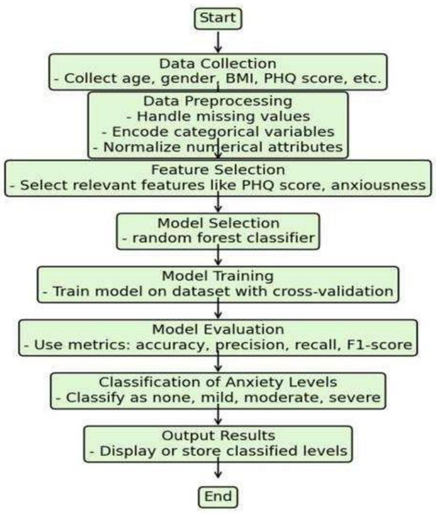

Fig. 1: Block diagram of Components

1. **Start:** This is where the process begins. It's like pressing the "Go" button to start analysing anxiety levels.

2. **Collecting Data:** First, we need to gather important details about a person, such as:

- **Age** – Anxiety might affect different age groups differently.
- **Gender** – Some studies suggest that anxiety patterns vary between men and women.
- **BMI (Body Mass Index)** – Physical health can sometimes be linked to mental well-being.
- **PHQ Score (Patient Health Questionnaire)** – A common test used to measure anxiety and depression levels.

3. **Preparing the Data** (Data Preprocessing): Before we can train a model, we need to clean and organize the data:

- **Fix missing data** – If some information is missing, we fill in the gaps or remove incomplete entries.
- **Convert words into numbers** – Computers work best with numbers, so we convert text-based data (like gender) into numerical values.
- **Make numbers consistent** – We adjust numerical values so they're all on a similar scale, preventing any one factor from dominating the results.

4. **Choosing the Most Important Data** (Feature Selection): Not all collected information is useful, so we pick only the most relevant details:

- **PHQ Score** – This directly measures anxiety levels.
- **Anxiousness-related symptoms** – Things like sleep issues, concentration problems, or constant worry.

5. **Choosing the Best Model:** We need a machine-learning model to make predictions. In this case, we use the **Random Forest Classifier** because:

- It gives **accurate results** by combining multiple decision trees.
- It works well with different types of data.
- It prevents **overfitting**, meaning it will not just memorize the data—it will learn from it.

6. **Training the Model**

- Now, we feed our cleaned and selected data into the model so it can learn patterns.
- We also use **cross-validation**, which means we train the model multiple times on different sections of the data to make sure it works well in various situations.

7. **Checking If the Model Works Well** (Evaluation): After training, we test how well the model predicts anxiety levels using different measures:

- **Accuracy** – How often the model gets it right.
- **Precision** – Out of the cases where the model says a person has anxiety, how many are correct?
- **Recall** – Out of all the people who have anxiety, how many does the model correctly identify?
- **F1-score** – A balanced score that considers both precision and recall.

8. **Classifying Anxiety Levels:** Based on the model's predictions, we classify people into one of four anxiety levels:

- **None** – No noticeable signs of anxiety.
- **Mild** – Some symptoms, but manageable without major intervention.
- **Moderate** – Noticeable anxiety that might need professional support.
- **Severe** – High anxiety levels requiring urgent attention.

9. **Displaying or Storing the Results:** Once the anxiety level is classified, the results can be:

- **Shown to the user** (for example, in an app or report).

- **Saved in a database** for future tracking and trend analysis.

10. **End:** The process is complete, and we now have a clear idea of the anxiety levels for the individuals being assessed.

1.2 FLOW DIAGRAM OF THE PROJECT

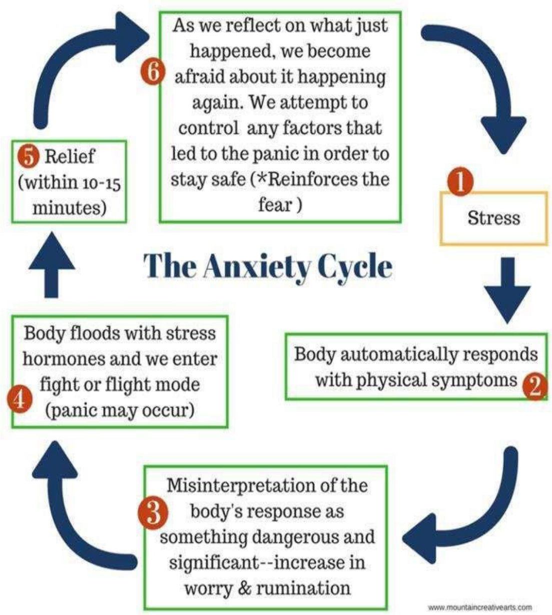

Fig. 2: Anxiety Level Classification System

The anxiety-level classification system involves multiple stages to process input data, extract features, and classify anxiety levels based on predefined parameters. Below are the detailed steps involved in the system workflow:

Step 1: Stress

- Anxiety often begins with **stress**, which can be triggered by anything—an upcoming exam, a difficult conversation, or even an unexpected situation.
- Your mind perceives this stress as a **potential threat**, even if it is not something physically harmful.
- This initial stress **activates** your body's natural defence system, preparing you to react.

Step 2: Physical Symptoms Appear

- Once stress kicks in, your body **automatically responds** with physical symptoms like a racing heart, shortness of breath, sweating, or dizziness.
- These symptoms happen because your nervous system is **on high alert**, preparing for a fight-or-flight response.
- Even if the situation is not actually dangerous, your body reacts as if it is.

Step 3: Misinterpreting the Body's Reaction

- Instead of recognizing these symptoms as a normal reaction to stress, the brain often **misunderstands them** as signs of something more serious.
- This misinterpretation leads to **increased worry**, making you think something is seriously wrong—like having a panic attack or a health problem.
- The more you **focus on the symptoms**, the more anxious you feel, making the cycle continue.

Step 4: Fight-or-Flight Mode Activates

- As anxiety escalates, your body floods with stress hormones like adrenaline and cortisol.
- This triggers the fight-or-flight response, which is meant to protect you in real danger.
- However, since the perceived threat is not always real, this reaction can feel overwhelming leading to panic, racing thoughts, or a sense of losing control.

Step 5: Temporary Relief

- After about **10-15 minutes**, your body starts to calm down as the stress hormones decrease.
- You might feel exhausted but relieved that the intense anxiety is fading.
- However, since the anxiety **did not fully resolve**, the brain remains on guard, making you more sensitive to future triggers.

Step 6: Fear of It Happening Again

- Once the anxiety episode passes, the mind starts **overanalysing** what just happened.
- You might start avoiding situations that triggered the anxiety, fearing it could happen again.
- This attempt to **control or prevent future anxiety** actually reinforces the cycle—making fear stronger over time.

IMPLEMENTATION

An anxiety-level classification system utilizes a robust infrastructure to process data, extract features, and classify anxiety levels. This system ensures scalability and accuracy while maintaining data privacy and security. By leveraging machine-learning algorithms, the classification system offers enhanced control, efficiency, and reliability.

Users benefit from an anxiety classification system by securely storing and processing sensitive mental health data. The system empowers administrators to maintain full control over data access and storage capacity while ensuring scalability to accommodate large datasets.

SYSTEM SETUP

Step 1: Data Collection: Gather data from various sources, including demographic factors (e.g., age, gender), physiological signals (e.g., heart rate, sleep patterns), and mental health indicators (e.g., BMI, depression severity). Ensure ethical guidelines are followed for data collection, including informed consent and privacy protection.

Step 2: Data Preprocessing: Remove noise and artifacts from the collected data to improve quality. Normalize and standardize the data to ensure compatibility across all input features. Handle missing data using imputation techniques.

Step 3: Feature Extraction: Extract relevant features indicative of anxiety, such as heart rate variability, sleep quality metrics, and survey scores. Use statistical and signal-processing techniques to refine the feature set.

Step 4: Model Training and Deployment: Utilize machine-learning tools such as Support Vector Machines, Random Forest, and Neural Networks to train models using a labelled dataset. Validate the models with test data to ensure high accuracy and reliability. Deploy the trained model on a secure computational platform.

Step 5: System Testing and Optimization: Test the system with sample inputs to verify accuracy and consistency. Optimize the models and system architecture for performance and scalability.

Step 6: Output and Insights: Generate and present anxiety level predictions categorized as Severe, Moderate, Mild, or No Anxiety. Provide visual insights through graphs and reports to aid in decision-making.

RESULT

With the implementation of this anxiety level classification system, we have successfully developed an accessible and effective method for remotely assessing and classifying individuals' anxiety levels. The system ensures data privacy and accuracy while utilizing machine-learning algorithms to analyse a variety of inputs, including demographic and physiological data. This solution empowers users and healthcare professionals to monitor mental health in a non-intrusive way, providing a reliable alternative to traditional methods of anxiety detection and early intervention.

COMAPARISION OF DIFFERENT MODELS ACCURACY

The main purpose of our project was about trying out different models and analysing their accuracy out of all the models Random Forest and Decision Tree has the highest accuracy.

Sl.no	MODELS	ACCURACY
1	Random forest	87.91
2	Decision Tree	86.60
3	Gradient Boosting	85.95
4	K-Nearest neighbours	66.34
5	Gaussian Naive Bayes	61.44
6	Ada Boosting	53.92

CONCLUSION

The anxiety level classification system integrates advanced machine-learning techniques such as Support Vector Machines, Random Forest, and Neural Networks to analyse a variety of key indicators—age, gender, BMI, heart rate, sleep patterns, and depression severity. These metrics, gathered through data collection, help the system accurately classify anxiety levels. The goal is not only to provide early detection of anxiety but also to enable automated, personalized assessments. By using this system, individuals can better understand their mental health, receive timely intervention, and foster ongoing awareness, leading to improved well-being and proactive care.

REFERENCES

[1]. Early Prediction and Detection of Anxiety Level Using Support Vector Machine by Tisha Sadariya and Shanti Verma.

[2]. Detection and classification of anxiety in university students through the application of machine-learning by Shaurya Bhatnagar, Jyoti Agarwal, Ojasvi Rajeev Sharma.

[3]. Anu Priyaa, Shruti Garga, Neha Prerna Tigga (2019). Predicting Anxiety, Depression and Stress in Modern Life using Machine-learning Algorithms

[4]. Abbas J et al (2021) The role of social media in the advent of COVID-19 pandemic: crisis management, mental health challenges and implications. Risk Manage Healthcare Policy:1917–1932

[5]. A Deep-learning-Based Comparative Study to Track Mental Depression from EEG Data," authored by S. S. Kumar, S. S. Kumar, and S. S. Kumar, published in 2021

[6] Sawhney, Manisha, Seth Kunen, and Ashum Gupta (2018) "Depressive Symptoms and Coping Strategies Among Indian University Students." Psychological Reports 123(2): 266-280.

[7] Na, Kyoung-Sae, Seo-Eun Cho, and Seong-Jin Cho. (2021) "Machine-learning-based discrimination of panic disorder from other anxiety disorders." Journal of Affective Disorders, 278:1–4.

[8] Anbarasi, L. Jani, Malathy Jawahar, Vinayakumar Ravi, and Sherin M. Cherian. (2022) "Machine-learning Approach for anxiety and sleep disorders analysis during COVID-19 lockdown", Health and Technology 12(4): 825–838.

[9] Kessler, Ronald C, Ayelet Meron Ruscio, Katherine Shear, and Hans-Ulrich Wittchen (2009) "Epidemiology of Anxiety Disorders". Behavioral Neurobiology of Anxiety and Its Treatment: 21-35.

[10] Swain, Prafulla Kumar, Manas Ranjan Tripathy, Subhadra Priyadarshini, and Subhendu K. Acharya (2021) "Forecasting suicide rates in India: An empirical exposition". PLOS ONE 16(7):1-21.