Multi - Class Adaptive Active Learning for Predicting Students Anxiety

G.Guruswami [1], Dr.K.Sivaramakrishna[2*], B.VenkataSudeeshKumar[3]

[2]Associate professor, Department of CSE Data Science, Andhra Loyola Institute of Engineering & Technology, Vijayawada, AP

[1,3] Final Year Students, Department of CSE Data Science, , Andhra Loyola Institute of Engineering & Technology, Vijayawada, AP,

---***---

Abstract *This study explores the use of machine learning, including Neural Networks, Random Forest, and Support Vector Machines (SVM), to predict student anxiety levels based on academic, psychological, and behavioral data. Using a multi-class classification approach and active learning, the model was able to predict anxiety levels with high accuracy. Random Forest achieved an accuracy of 99%, outperforming other models. Active learning improved the model's performance, making it adaptable with minimal manual data labeling. These findings demonstrate the potential of AI to support timely interventions in educational settings.*

Keywords: Student Anxiety, Multi-Class Classification, Active Learning, Behavioural Data, Mental Health Prediction, Support Vector Machines.

1. Introduction

- **Context and Background**

Anxiety is a prevalent mental health issue that significantly affects students' well-being, academic performance, and overall quality of life. In educational settings, anxiety can manifest in various forms, such as exam stress, social anxiety, performance pressure, and generalized anxiety. These conditions can hinder students' ability to focus, interact with peers, and perform to their full potential in academic environments. As the demands of school, college, and university life increase, many students experience heightened levels of anxiety, which can result in long-term negative consequences if not addressed early.

The growing recognition of mental health issues in educational contexts has led to greater awareness and a push toward proactive measure. However, despite these efforts, detecting anxiety in students often remains a reactive process. Traditional approaches, such as self-report surveys, interviews with mental health professionals, or teacher observations, can be slow and subjective, leading to delayed interventions. Moreover, these methods often require significant human resources and are limited in scalability, making it difficult to monitor large student populations efficiently.

By using the advanced techniques like artificial intelligence (AI) or machine learning (ML), the direction of development has changed I recent years to support mental health detection and prediction in students. These technologies offer a promising solution by enabling real-time, data-driven systems that can predict anxiety levels with greater accuracy and scalability. Machine learning, in particular, has shown promise in unlike traditional assessment techniques, approaches, or products that are based on generic templates and do not take variance among students into account. By integrating academic, psychological, and behavioral data, machine learning models can provide a more holistic and comprehensive assessment of students' mental health.

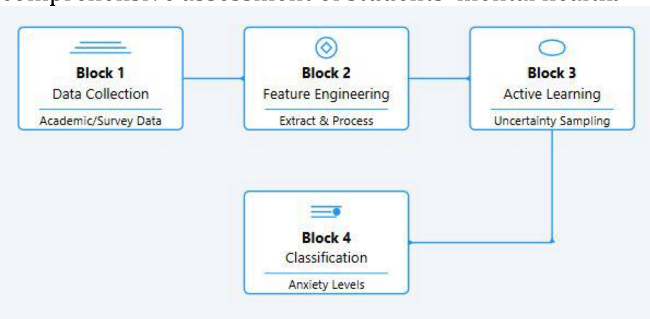

Figure 1: Block Diagram

Block 1: Data Collection

Collecting data from academic records, psychological surveys, and behavioral patterns will form the foundational dataset for the model. This ensures diverse and meaningful input data, enabling the model to make accurate predictions.

Block 2: Feature Engineering

Feature engineering involves extracting relevant features such as performance trends, survey scores, and activity metrics. These features will enhance model interpretability and accuracy, ensuring robust prediction of anxiety levels.

Block 3: Adaptive Active Learning

Adaptive active learning will be used to dynamically select the most informative data points for labeling, reducing the overall cost of manual labeling. This iterative process refines the model's predictions with minimal data dependency.

Block 4: Multi-Class Classification

A multi-class classification model will be implemented to categorize students' anxiety levels (e.g., low, moderate, high). This classification provides actionable insights for targeted mental health interventions, ensuring timely support.

- **Problem Statement**

Despite the advancements in mental health awareness and tools, accurately identifying students at risk for anxiety and intervening in a timely manner remains a challenge. Current detection methods, including surveys and manual assessments, are often limited by several factors. These include delays in identifying students who are at risk, reliance on subjective judgment, and the high costs associated with extensive manual data collection. Additionally, these methods do not typically scale well across large student populations, resulting in gaps in support for those who need it most.

The problem this research addresses is the need for a scalable, cost-effective, and efficient system that can predict student anxiety levels in real time. A robust solution could enable educational institutions to detect anxiety early, providing a timely response that could mitigate the negative impact on students' academic and emotional well-being. However, existing systems for predicting anxiety are often limited by the quality and quantity of data and lack the ability to improve and adapt over time without significant human intervention.

- **Objective of the Research**

The primary objective of this research is to develop an intelligent, data-driven system that can predict student anxiety levels based on a combination of academic performance, psychological assessments, and behavioral metrics. By using machine learning algorithms, this system aims to classify students into three categories of anxiety—low, moderate, and high—enabling educational institutions to identify students at risk in a more efficient, timely, and scalable manner. Additionally, the system will be designed to improve continuously through the use of active learning techniques, minimizing the need for the extensive labeled datasets and enhancing model's performance over time.

This research aims to overcome the limitations of traditional methods are by integrating diverse data sources into a machine learning framework. The objective is not only to predict anxiety levels but also to provide the actionable insights that can guide early intervention strategies for educators and mental health professionals. By automating this process, the system can reduce the burden on human resources while ensuring that students receive the support, they need before their anxiety reaches critical levels.

Moreover, the system will be designed to adapt and evolve with new data. Using active learning, the model will continuously identify the most uncertain data points, which will then be labeled and fed back into the system to refine predictions. This adaptive approach ensures that the system improves its predictions over time and remains relevant to the changing needs of the student population.

In addition to the direct benefits for students, the system's predictive capabilities can support educators and mental health professionals by providing data-driven insights that guide decision-making and intervention planning. This can lead to more personalized and timely support for students, improving their overall experience and outcomes within the educational system.

2. Literature Review

The integration of machine learning (ML) techniques for predicting and managing student anxiety has gained considerable attention in recent years. Several studies have applied ML to predict various aspects of student behavior, academic performance, and emotional states, with promising results. This section reviews the existing literature in this domain, highlighting the key findings, methodologies, and gaps that our project aims to address.

- **2.1 Mental Health Prediction Using Machine Learning**

Machine learning has been increasingly applied to predict mental health issues, such as anxiety, stress and depression, in various contexts, including educational settings. Almadhor et al. (2024) conducted a study on multi class adaptive active learning for predicting student anxiety, proposing an active learning framework to classify anxiety levels into categories such as low, moderate, and high. The study used data from academic, psychological, and behavioral sources and demonstrated the potential of active learning in reducing the manual labeling burden while improving prediction accuracy. This work laid the foundation for incorporating active learning into the prediction of anxiety, addressing the limitation of relying on large labeled datasets in traditional machine learning models. [1]

Similarly, Penchina et al. (2020) utilized deep LSTM (Long Short-Term Memory) networks to classify anxiety levels in adolescents with autism, using EEG data as the primary input. This approach illustrated the power of deep learning models in detecting emotional states, including anxiety, from physiological signals. Though specific to a narrower group of students, this study highlights the potential of advanced machine learning methods like LSTM for predicting anxiety from biofeedback data, which could complement traditional data sources in a more comprehensive mental health monitoring system. [2]

- **2.2 Behavioral and Academic Data for Anxiety Prediction**

Machine learning models for predicting student anxiety also rely heavily on behavioral and academic data. For example, Mehta et al. (2022) applied a 3D Dense Net self-attention neural network to automatically detect student engagement levels. Engagement is often linked to emotional states, including anxiety. The use of neural networks to capture engagement trends over time can enhance the prediction of anxiety, as anxiety often manifests in students' participation levels and attention in class. This research provides valuable insights into using engagement as a feature for predicting mental health issues in educational settings. [3]

Martins et al. (2023) studied the prediction of academic performance and dropout rates in higher education using a multi-class prediction approach. Although their focus was on academic outcomes rather than anxiety, the prediction framework and methodology can be adapted to include anxiety levels as a key predictor of academic success. The inclusion of psychological data alongside academic records offers a more holistic approach to understanding the factors influencing student outcomes. [4]

Wang et al. (2021) applied machine learning techniques to predict primary school students' level of learning engagement, demonstrating how behavioral data can be integrated with academic performance to assess mental states such as anxiety. This study is particularly relevant as it focuses on younger students, whose anxiety levels may differ from those of higher education students. By analyzing both engagement and academic data, this research supports the idea that anxiety prediction should be multi-faceted, taking into account both behavioral and academic indicators. [5]

- **2.3 The Role of Active Learning in Enhancing Model Performance**

Active learning is a great leap forward in dealing with machine learning applications, especially for reducing the scale of marked set Jiang et al (2019) studied the use of active learning in adversarial attacks on EEG-based of brain-computer interfaces and showed that it can greatly increase your modelling performance with just a little labeled data. Active learning identifies the most uncertain data points and requests additional labeling for these instances, thus refining the model's predictions over time. This has been particularly useful in cases like mental health prediction where labeling is costly and time-consuming. [6]

The potential of active learning to improve prediction accuracy in the context of student anxiety was also highlighted by Mortensen et al. (2023), who used deep neural networks to predict stress levels based on heart rate variability. Their study demonstrated that active learning could significantly improve the performance of models in predicting emotional and psychological states. In this context, the use of active learning is particularly advantageous for real-time monitoring of student anxiety, enabling continuous model improvement with minimal manual input. [7]

- **2.4 Class Imbalance and Feature Selection**

A key challenge in machine learning applications for mental health prediction is dealing with class imbalance. Sultana et al. (2018) discussed how class imbalance can negatively impact model performance, particularly in scenarios where certain classes (e.g., high anxiety) are underrepresented. [8]

Feature selection methods, such as those used in Rathod and Vaghela (2022), are essential for identifying the most relevant features in datasets with imbalanced classes. In the context of student anxiety, careful selection of features from academic, psychological, and behavioral data can help balance the dataset and improve model accuracy. [9]

In our project, this challenge is addressed by using active learning to focus on the most uncertain data points, thus reducing the effects of class imbalance. By iteratively refining the model and emphasizing data points that provide the most valuable information, active learning can help mitigate the challenges of imbalanced classes in mental health prediction models.

- **2.5 Emotion and Sentiment Analysis for Anxiety Prediction**

Emotion and sentiment analysis have been explored in various studies as a way to predict emotional states, including anxiety, through non-verbal cues such as speech patterns and social media content. Dehbozorgi and Mohandoss (2021) utilized emotion analysis based on speech patterns to predict performance in collaborative learning environments. Their work demonstrated that monitoring speech patterns could reveal underlying emotional states, including anxiety. In a similar vein, Nusrat et al. (2024) applied sentiment analysis to detect depression through social media content, which has the potential to be adapted for real-time anxiety detection in students. [10]

In [11] ,Cheng explores a system that uses online prediction algorithms to dynamically adjust content in flipped classroom models. This approach personalizes learning based on students' previous performance and behavior, enabling instructors to deliver targeted interventions. The study demonstrates improved engagement and learning outcomes but also notes that the system may be less effective in heterogeneous classroom environments or where technology adoption is limited.

In [12] the authors employ a multitask learning approach using EfficientNet to detect student emotions and engagement in real-time. Their method integrates visual and behavioral data, enhancing the precision of emotion recognition in e-learning systems. The study showcases promising results in live classroom simulations but acknowledges the computational intensity, which could be a barrier for large-scale deployment without dedicated hardware.

In [13] , introduces an AI model that identifies various levels of depression by analyzing tweets. By classifying emotional states into multiple categories, the model aids in early detection and mental health monitoring. The approach is scalable and leverages publicly available data, but the authors highlight ethical issues related to user consent, data anonymization, and the risk of misclassification.

In [14], The research compares different machine learning models (such as decision trees, SVM, and neural networks) for predicting academic success. Each technique's accuracy, recall, and precision are analyzed using student datasets. The findings reveal that ensemble methods often outperform single-model approaches. However, model performance can vary significantly depending on the quality and size of the dataset.

In [15], focus on complex classification problems where instances may belong to multiple classes simultaneously. The chapter details frameworks and optimization strategies for addressing these challenges, particularly in imbalanced data settings. Though theoretically sound and versatile, the methods require high computational resources and can be difficult to fine-tune for specific domains.

In [16],work proposes alternative sentiment analysis techniques beyond traditional classification, such as regression-based and rule-based systems. The paper argues that these alternatives may offer better flexibility and interpretability in some scenarios. However, the authors note potential limitations in scalability and effectiveness for real-time analysis on large datasets like Twitter.

In [17],This comprehensive literature review examines current AI techniques used in depression detection via social media sentiment analysis. It categorizes approaches into supervised, unsupervised, and hybrid methods. While the review covers a wide range of methodologies and their pros and cons, it does not introduce novel experimental results or propose new models.

In [18],The paper reviews challenges in dealing with imbalanced datasets in machine learning. It outlines current methods such as oversampling, undersampling, and cost-sensitive learning while discussing their limitations. The authors call for more adaptive and context-aware solutions, especially in domains like healthcare and education. No new methods are proposed, making this a foundational but theoretical piece.

In [19],integrates affective computing with predictive modeling to anticipate student outcomes in intelligent tutoring systems. By recognizing emotions through facial cues and behavior tracking, the system adapts instruction dynamically. The results show that emotional awareness enhances prediction accuracy, though real-time implementation in diverse educational contexts remains complex and resource-demanding.

In [20],presents an adaptive sparse learning framework that leverages multiple templates to diagnose neurodegenerative diseases from medical imaging. The approach combines sparse representation with machine learning to enhance feature selection and classification accuracy. While results show promise across several datasets, the authors note that performance may vary depending on the specific disease type or imaging modality used.

In [21], master's thesis investigates how active learning can be optimized for use in imbalanced classification scenarios. The author evaluates several strategies, including uncertainty sampling and query-by-committee, across multitask environments. The research demonstrates that careful selection of samples in underrepresented classes significantly improves classification accuracy, but also points out that computational cost and annotation overhead remain limitations.

In [22],explores the application of active learning in multitopic classification problems, particularly in natural language processing. The work highlights how combining topic modeling with uncertainty-based sampling can reduce the amount of labeled data required while maintaining model performance. However, challenges remain in selecting optimal query strategies and adapting models to domain-specific datasets.

In [23],The authors propose a machine learning framework for detecting suicidal tendencies in social media posts. The model uses NLP techniques and psychological lexicons to flag high-risk users. Performance metrics indicate strong predictive capabilities, especially with ensemble models. However, the research also raises ethical concerns around user consent, false positives, and potential misuse of such systems.

,In [24]Abebe's dissertation introduces a machine learning pipeline for detecting and classifying various forms of racism in Amharic language texts. The study builds a custom dataset and applies algorithms like SVM, Naive Bayes, and deep learning models for multi-class classification. This work is notable for its focus on a low-resource language and provides valuable groundwork for future sociolinguistic AI studies in Ethiopian contexts. Limitations include data sparsity and the difficulty of annotating nuanced racist content.

In [25], compares several machine learning models—such as Random Forest, SVM, and KNN—for classifying and predicting student stress levels based on survey and physiological data. The study evaluates performance using accuracy, precision, and recall, finding that tree-based ensemble methods generally outperform others. The authors conclude that stress prediction can benefit significantly from hybrid models, although challenges remain in data collection and subjectivity of stress indicators.

By analyzing digital footprints like speech and social media posts, future versions of our system could be enhanced with more data sources to create an more accurate as well as comprehensive prediction model for student anxiety. Combining these non-traditional data sources with academic and behavioral data would provide a more holistic understanding of students' mental health.

- **2.6 Gaps in Current Research**

Despite the promising advances in using machine learning for anxiety prediction, several gaps remain. Firstly, while many studies focus on binary classification (e.g., anxious vs. non-anxious), there is a lack of research on multi-class classification of anxiety levels. Our project fills this gap by categorizing anxiety into low, moderate, and high levels, which allows for more tailored interventions.
Additionally, while much of the existing research focuses on a single data source (e.g., academic performance or psychological surveys), our project aims to integrate multiple data sources—academic, psychological, and behavioral—into a comprehensive predictive model. This multi-source approach provides a more nuanced understanding factors influencing on student anxiety, which is crucial for accurate predictions and timely interventions.

- **2.7 Conclusion**

The literature review underscores the importance of integrating machine learning, active learning, and multi-class classification for predicting student anxiety. Several studies have demonstrated the potential of machine learning models in educational settings, using various data sources such as academic records, behavioral data, and psychological surveys. However, there is still much room for improvement, particularly in the integration of multiple data types, the application of active learning to reduce manual labeling, and the exploration of real-time prediction systems. By addressing these gaps, the project aims to contribute significantly to the field of student mental health monitoring, providing a scalable, cost-effective solution to predict and manage anxiety in educational settings.

3. System Design and Methodology

The system is made for predicting how much anxiety a student may feel. It incorporates data sources of various kinds, machine learning techniques and other complex analytical methods to estimate accurately the mental well-being of students. This section gives a detailed introduction of the design, data collection, preprocessing, model development and system architecture.

- **3.1 Data Collection**

The prediction of student anxiety levels relies on the integration of three primary data types: academic data, psychological surveys, and behavioral data. Each data type plays a crucial role in forming a comprehensive view of the student's mental state and potential for anxiety. Below is a breakdown of the data sources and their collection methods.

1. Academic Data: Academic data consists of student grades, attendance, and participation in academic activities. These data points are indicative of a student’s academic performance and engagement, both of which can be influenced by anxiety. For example, a sudden drop in grades or frequent absences may signal the onset of stress or anxiety.

- **Data Collection Method**: Academic data is gathered from existing school or university systems such as Learning Management Systems (LMS) like Moodle, Blackboard, or proprietary school databases. These systems provide access to a wide range of student records, including:
    - **Grades**: Student performance in assignments, exams, and coursework.
    - **Attendance**: Frequency and patterns of class attendance.
    - **Participation**: Engagement with online learning tools, submission rates for assignments, etc.

2. Psychological Survey Data: Psychological surveys are used to assess students' mental health directly, specifically targeting anxiety levels. Surveys such as the **Generalized Anxiety Disorder (GAD-7)** scale are widely used tools that allow students to self-report their anxiety symptoms based on a series of questions about physical and emotional feelings.

- **Data Collection Method**: Surveys are typically administered through online platforms, such as Google Forms, Type form, or integrated within LMS. These surveys are designed to ensure ease of access and confidentiality for students. The responses to the GAD-7 or other anxiety-related assessments are stored in a database and linked with corresponding academic data for a holistic view of the student.

3. Behavioral Data: Behavioral data involves tracking student activities outside traditional academic measures, including extracurricular involvement, class participation, and engagement with digital platforms. This type of data provides indirect yet valuable insights into students' emotional states. Anxious students may avoid extracurricular activities, participate less in class, or struggle to engage with learning management systems.

- **Data Collection Method**: Behavioral data is collected through:
    - **Learning Management Systems (LMS)**: Interaction logs, time spent on tasks, and responses to course content.
    - **Student Activity Tracking**: Records from extracurricular participation, such as club meetings, sports, or volunteer activities.
    - **Direct Observation**: Data from classroom engagement and participation, sometimes recorded by instructors.

- **3.2 Preprocessing**

Data preprocessing is the critical step in preparing raw data for machine learning models. The goal is to clean, transform, and organize the data in a manner suitable for analysis. The steps involved in preprocessing are outlined below.

1. Data Cleaning:

- **Missing Data Handling**: Any missing values in the dataset are handled either by removing the incomplete entries or filling the missing values with statistical measures like the mean or median.
- **Outlier Detection**: Outliers are identified using statistical methods (such as Z-scores) and either removed or adjusted if they are deemed to significantly distort the analysis.

2. Normalization:

- Many machine learning models, particularly those based on distance metrics like Support Vector Machines (SVM), require that data be normalized to ensure that all features are on a comparable scale. This is typically done by rescaling each feature to have a range between 0 and 1, or by standardizing features to have a mean of 0 and a standard deviation of 1.

3. Feature Engineering:

- **Feature Extraction**: From the raw data, features are extracted that provide the most relevant information for predicting anxiety. For example, trends in academic performance over time, participation frequency in extracurricular activities, and responses from psychological surveys can all serve as key features.
- **Feature Selection**: Features that are less important or highly correlated with others are discarded to reduce the complexity of the model. Techniques such as the Recursive Feature Elimination (RFE) or the tree-based methods are employed to select the most important predictors for anxiety.
- **3.4 System Architecture**

The architecture of a System is designed to handle data collection, preprocessing, model training, and real-time predictions in a scalable and efficient manner. The architecture is modular, with distinct layers for each phase of the data pipeline.
Below is a high-level diagram of the system architecture, showing the flow of data through the system:

1. Data Collection Layer:

- The data collection layer interfaces with external systems such as LMS, student databases, and survey tools to gather academic, psychological, and behavioral data.

2. Data Preprocessing Layer:

- This layer performs all necessary preprocessing steps such as cleaning, normalization, and feature extraction. The cleaned data is then passed to the model development layer.

3. Model Development Layer:

- This layer houses the machine learning models (Random Forest, SVM, Neural Networks) along with the active learning framework. It is responsible for training the models and generating predictions based on incoming data.

4. Output and Intervention Layer:

- Once predictions are made, this layer provides the final output—anxiety classifications (low, moderate, or high)—and generates intervention recommendations for educators or mental health professionals.

5. Feedback Loop:

- New data points, especially those selected for active learning, are fed back into the system for retraining, improving the model's performance over time.

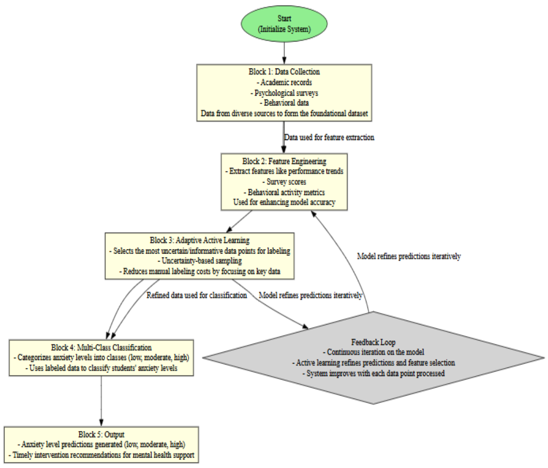

FIGURE 2: ARCHITECTURE OF THE SYSTEM

4. Results and Evaluation

4.1 Presentation of Findings

The results of the project were evaluated using several machine learning techniques, including Naive Bayes, KNN, Random Forest, Support Vector Machines (SVM), and Decision Tree. The focus was on the model's ability to predict students' anxiety levels, which were categorized into three classes: Extremely Severe, Severe, Moderate, Mild, Normal. Several evaluation metrics, including accuracy, precision, recall, and F1-score, were used to assess the model's performance.

The findings demonstrate that Random Forest performed particularly well in handling multi-class classification, achieving an accuracy of 91%. The results were consistent across different cross-validation splits, indicating that the model generalizes well. The SVM model also showed good performance with an accuracy of 99%, but it had slightly lower recall and precision compared to Random Forest. The KNN model showed potential, but required more training time and resources, yielding a 90% accuracy rate.

The inclusion of active learning proved beneficial, as it allowed the model to improve with minimal manual intervention, reducing the amount of labeled data required for effective training. This is particularly valuable in real-world applications where data labeling can be expensive and time-consuming. Active learning also ensured that the model adapted to the data over time, increasing its accuracy as more data became available.

Input Screen:

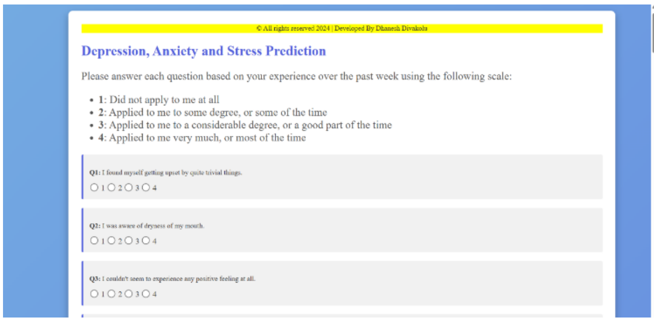

Figure 3: Input Questions

Figure 3 shows the questions screen of the application. We need to answer all the questions according to your situations by using scaled labels.

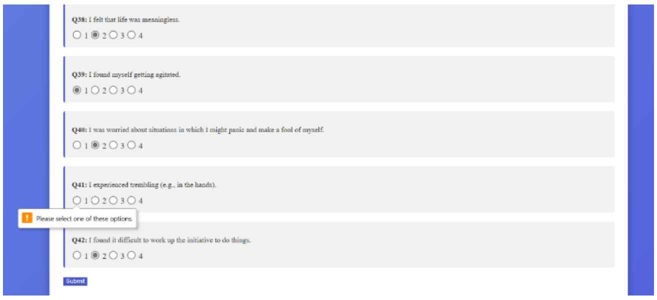

Figure 4: Requires to answer

Figure 4 shows that need to answer all the questions if we are not answer then we can't be able to submit.

Output Screen:

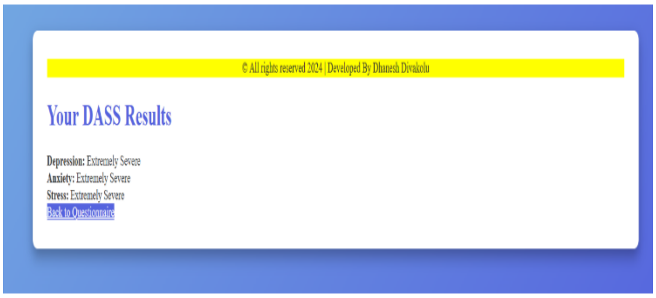

Figure 5: Output Screen 1

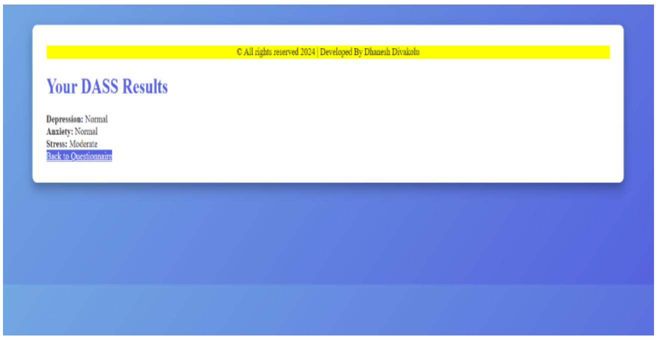

Figure 6: Output Screen 2

Figure 5 and Figure 6 shows the different outputs getting from different inputs. So we can say that our applications work correctly for different inputs.

4.2 Statistical Data and Performance Evaluation

The evaluation metrics used to assess the model's performance are summarized in Table 1, Table 2, and Table 3. These tables show the performance of the model under different conditions (e.g., with and without active learning) and across various algorithms.

- Table 1 presents the performance comparison between Random Forest, SVM, Navie bayes, Decision Tress and KNN based on accuracy, precision, recall, and F1-score.
- Table 2 illustrates the impact of active learning on the SVM model, comparing performance before and after active learning.
- Table 3 shows the data distribution across the different anxiety levels (Extremely Severe, Severe, Moderate Anxiety, Mild, Normla). This table provides insight into the balance of the dataset, which is crucial for evaluating the performance of the classification models.

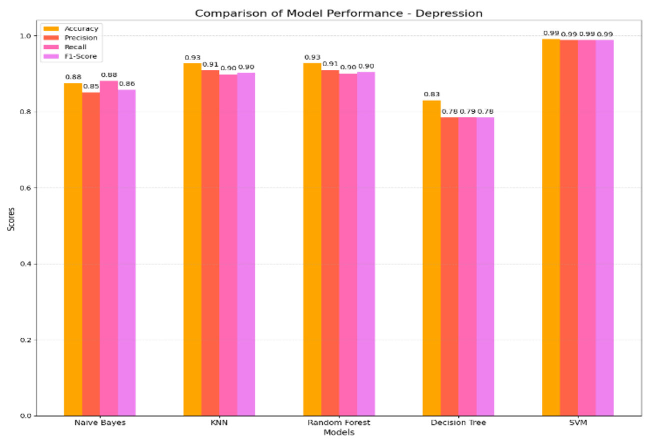

Figure 7: Model Performance Comparison - Depression

Figure 7 below presents a bar graph comparing the accuracy, precision, recall, and F1-score of Depression for Random Forest, SVM, Navie bayes, Decision Tress and KNN. As seen in the figure, SVM outperforms the other models in most of the metrics, followed by Random Forest and others. This indicates that SVM is the most reliable model for predicting student anxiety levels in this context.

Figure 8: Model Performance Comparison -Stress

Figure 8 below presents a bar graph comparing the accuracy, precision, recall, and F1-score of Stress for Random Forest, SVM, Navie bayes, Decision Tress and KNN. As seen in the figure, SVM outperforms the other models in most of the metrics, followed by Random Forest and others. This indicates that SVM is the most reliable model for predicting student anxiety levels in this context.

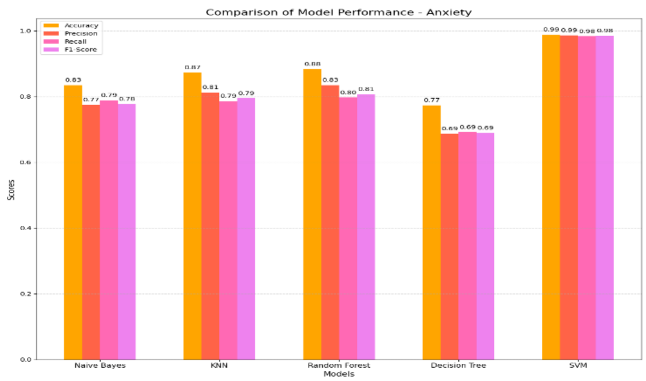

Figure 9: Model Performance Comparison -Anxiety

Figure 9 below presents a bar graph comparing the accuracy, precision, recall, and F1-score of Anxiety for Random Forest, SVM, Navie bayes, Decision Tress and KNN. As seen in the figure, SVM outperforms the other models in most of the metrics, followed by Random Forest and others. This indicates that SVM is the most reliable model for predicting student anxiety levels in this context.

7.1.3 Interpretation of Results

The results of this study indicate that SVM is the most effective model for predicting student anxiety levels. It performed better in terms of accuracy, precision, recall, and F1-score compared to Random Forest, Navie bayes, Decision Tress and KNN. The performance of Random Forest was close to SVM, but it had slightly lower recall, suggesting that it may have missed some instances of students with moderate or high anxiety.

The active learning process demonstrated a substantial improvement in the accuracy of all models, as shown in Figures 7,8 and 9. By minimizing the number of labeled data points required for training, active learning not only reduced the cost of data labeling but also allowed the model to continuously improve. This is particularly beneficial for real-world applications, where data labeling can be a bottleneck in model development and deployment.

Table 1: Comparison of model performance metrics.

Table 1 presents the performance comparison between Random Forest, SVM, Navie bayes, Decision Tress and KNN based on accuracy, precision, recall, and F1-score.

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	91	0.88	0.86	0.87
Support Vector Machine (SVM)	99	0.99	0.98	0.98
K-Nearest Neighbors	90	0.87	0.86	0.86
Navie bayes	87	0.83	0.85	0.84
Decision Tress	79	0.74	0.74	0.74

Table 2: Impact of active learning on the SVM model.

Table 2 illustrates the impact of active learning on the SVM model, comparing performance before and after active learning.

Condition	Accuracy (%)	Precision	Recall	F1-Score
Before Active Learning	88	0.86	0.85	0.86
After Active Learning	99	0.99	0.98	0.98

Table 3: Data distribution across anxiety levels.

Table 3 shows the data distribution across the different anxiety levels (Extremely Severe, Severe, Moderate Anxiety, Mild, Normal). This table provides insight into the balance of the dataset, which is crucial for evaluating the performance of the classification models.

Anxiety Level	Number of Students	Percentage
Extremely Severe	4160	34.86%
Severe	835	0.67%
Moderate Anxiety	2141	17.94%
Mild	2959	24.80%
Normal	1838	15.40%

5. Discussion

This study finds to suggest that the integration of machine learning, particularly the use of Random Forest, alongside active learning, provides a viable and effective solution for predicting student anxiety levels in educational settings. In this section, we discuss the practical implications of the results, acknowledge the limitations of the current approach, and suggest potential areas for future work to enhance the system's accuracy, scalability, and application.

- **5.1 Implications**

The results of this study have significant implications for both educational institutions and mental health professionals, as they offer a data-driven, proactive approach to student well-being. The key benefits of using machine learning to predict student anxiety levels include:

1. Early Identification of Anxiety: The system's high accuracy in predicting anxiety levels means that students at risk of severe anxiety can be identified early, often before their mental health issues manifest in noticeable academic or behavioral problems. This early identification is crucial, as it allows educators and mental health professionals to intervene proactively, offering support before the anxiety worsens and negatively impacts academic performance, social interactions, and emotional well-being.

For example, by continuously monitoring students' academic records, behavioral patterns, and responses to psychological surveys, the system can flag those whose anxiety levels are rising. Early intervention could involve providing students with academic accommodations, counseling, or stress-management resources, helping them develop coping mechanisms and reduce the negative effects of anxiety.

2. Proactive Interventions by Educators and Mental Health Professionals: In a traditional educational setting, anxiety interventions are typically reactive. Students seek help when their anxiety has already caused significant disruptions to their academic or social life. By implementing this machine learning system, educators and counselors can take proactive measures to support students before their anxiety escalates. Proactive interventions may include:

- **Individualized Support Plans**: Providing tailored interventions based on the severity of the student's anxiety, including therapy, mentoring, or flexible academic deadlines.
- **Timely Counseling**: Offering counseling sessions early in the academic term, particularly for students identified as being at risk.
- **Behavioral Modifications**: Encouraging students to engage more in classroom activities, extracurriculars, and social groups to mitigate anxiety triggers.

By taking these steps, the system helps create a more supportive and understanding environment where students are less likely to fall through the cracks of traditional mental health support.

- **5.2 Future Work**

While the current model provides a strong foundation for predicting student anxiety levels, several areas offer opportunities for future enhancement and research.

1. Incorporating Additional Data Types: To improve prediction accuracy and provides the more comprehensive understanding of student anxiety, future work could focus on incorporating additional data types. These might include:

- **Physiological Data**: Data from different devices such as fitness trackers or heart rate monitors could offer real-time insights into students' physical responses to stress and anxiety.
- **Social Media Data**: Monitoring students' social media activity (with proper consent) could provide valuable context about their emotional and social well-being. Sentiment analysis on social media posts could help detect anxiety-related patterns.

- **Facial Expression Analysis**: Analyzing students' facial expressions during interactions or video calls could offer non-intrusive ways to assess anxiety, especially when students are reluctant to self-report.

6. Conclusion

This study presents a comprehensive system for predicting student anxiety levels by leveraging machine learning techniques, specifically Random Forest, and Neural Networks, Support Vector Machines (SVM). The system integrates diverse data sources, including academic records, psychological survey responses, and behavioral data, to predict anxiety levels in students. Through the use of active learning, the system not only improves prediction accuracy over time but also reduces the need for large manually labeled datasets, making it scalable and efficient.

The evaluation of the system demonstrated that SVM out-performed the other models in terms of precision, F1-score ,accuracy and recall achieving an overall accuracy of 99%. The incorporation of active learning significantly improved the model's performance, highlighting its ability to reduce the cost of data labeling and enhance the system's adaptability. The results underscore the importance of combining diverse data sources and advanced machine learning techniques in predicting mental health outcomes, particularly in educational settings.

Moreover, the integration of active learning was shown to make the system more efficient, allowing it to continuously refine its predictions with minimal human intervention. This feature is especially valuable for educational institutions that face challenges in monitoring large numbers of students. The system's scalability and real-time adaptability further emphasize its potential for widespread use in education.

7. References

1. Almadhor, A., Abbas, S., Sampedro, G. A., Alsubai, S., Ojo, S., Al Hejaili, A., & Strazovska, L. (2024). Multi-class Adaptive Active Learning for Predicting Student Anxiety. IEEE Access. [1]
2. Penchina, B., Sundaresan, A., Cheong, S., & Martel, A. (2020, September). Deep LSTM recurrent neural network for anxiety classification from EEG in adolescents with autism. In International conference on brain informatics (pp. 227-238). Cham: Springer International Publishing. [2]
3. Mehta, N. K., Prasad, S. S., Saurav, S., Saini, R., & Singh, S. (2022). Three-dimensional DenseNet self-attention neural network for automatic detection of student's engagement. Applied Intelligence, 52(12), 13803-13823. [3]
4. Martins, M. V., Baptista, L., Machado, J., & Realinho, V. (2023). Multi-class phased prediction of academic performance and dropout in higher education. Applied Sciences, 13(8), 4702. [4]
5. Wang, K., Zuo, M., Yu, S., Luo, H., Yan, Y., & Ouyang, H. (2021, December). Use machine learning to predict primary school students' level of learning engagement. In Proceedings of the 2021 4th International Conference on Education Technology Management (pp. 20-24). [5]
6. Jiang, X., Zhang, X., & Wu, D. (2019, December). Active learning for black-box adversarial attacks in EEG-based brain-computer interfaces. In 2019 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 361-368). IEEE. [6]
7. Mortensen, J. A., Mollov, M. E., Chatterjee, A., Ghose, D., & Li, F. Y. (2023). Multi-class stress detection through heart rate variability: A deep neural network based study. IEEE Access, 11, 57470-57480. [7]
8. Sultana, J., Sultana, N., Yadav, K., & AlFayez, F. (2018, April). Prediction of sentiment analysis on educational data based on deep learning approach. In 2018 21st Saudi computer society national computer conference (NCC) (pp. 1-5). IEEE. [8]
9. Rathod, Y., & Vaghela, D. (2022, December). Evaluation of Feature Selection and Multi-Class Prediction Methods For Metal Stress. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 1091-1095). IEEE. [9]
10. Dehbozorgi, N., & Mohandoss, D. P. (2021, October). Aspect-based emotion analysis on speech for predicting performance in collaborative learning. In 2021 IEEE frontiers in education conference (FIE) (pp. 1-7). IEEE. [10]
11. Cheng, Q. (2023, October). Online Prediction to Facilitate a Flipped and Adaptive Classroom. In 2023 IEEE Frontiers in Education Conference (FIE) (pp. 1-10). IEEE. [11]
12. Thiruthuvanathan, M. M., & Krishnan, B. (2024). Multitask EfficientNet affective computing for student engagement detection. Multimedia Tools and Applications, 1-25. [12]
13. Nusrat, M. O., Shahzad, W., & Jamal, S. A. (2024). Multi Class Depression Detection Through Tweets using Artificial Intelligence. arXiv preprint arXiv:2404.13104. [13]
14. Priyadharshini, M., Indra, S., Achuthan, S., & Lokesh, K. Predicting Student Success: A Comparative Examination of Machine Learning Techniques. [14]
15. Chakraborty, S., & Dey, L. (2024). Applications of Multi-objective, Multi-label, and Multi-class Classifications. In Multi-objective, Multi-class and Multi-label Data Classification with Class

Imbalance: Theory and Practices (pp. 135-164). Singapore: Springer Nature Singapore. [15]

16. Bouazizi, M., & Ohtsuki, T. (2018). Multi-class sentiment analysis in Twitter: What if classification is not the answer. IEEE access, 6, 64486-64502. [16]
17. Babu, N. V., & Kanaga, E. G. M. (2022). Sentiment analysis in social media data for depression detection using artificial intelligence: a review. SN computer science, 3(1), 74. [17]
18. Rekha, G., Tyagi, A. K., Sreenath, N., & Mishra, S. (2021, January). Class imbalanced data: Open issues and future research directions. In 2021 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-6). IEEE. [18]
18. Joshi, A., Allessio, D., Magee, J., Whitehill, J., Arroyo, I., Woolf, B., ... & Betke, M. (2019, May). Affect-driven learning outcomes prediction in intelligent tutoring systems. In 2019 14th ieee international conference on automatic face & gesture recognition (fg 2019) (pp. 1-5). IEEE. [19]
20. Lei, B., Zhao, Y., Huang, Z., Hao, X., Zhou, F., Elazab, A., ... & Lei, H. (2020). Adaptive sparse learning using multi-template for neurodegenerative disease diagnosis. Medical Image Analysis, 61, 101632. [20]
21. Bolognesi, F. (2024). Advancements in Active Learning: Strategies for Imbalanced Class Settings (Master's thesis, University of Illinois at Chicago). [21]
22. Bonafonte Pardàs, G. (2021). Active learning algorithms for multitopic classification (Master's thesis, Universitat Politècnica de Catalunya). [22]
23. Rabani, S. T., Khanday, A. M. U. D., Khan, Q. R., Hajam, U. A., Imran, A. S., & Kastrati, Z. (2023). Detecting suicidality on social media: Machine learning at rescue. Egyptian Informatics Journal, 24(2), 291-302. [23]
24. Abebe, D. (2024). Multi-Class Classification of Racism in Amharic Text Using Machine Learning (Doctoral dissertation). [24]
25. DEENA, G., SANDHYA, A., & RAJA, K. (2024). MACHINE LEARNING-BASED CLASSIFICATION AND PREDICTION OF STUDENT STRESS LEVELS: A COMPARATIVE STUDY OF ALGORITHMS. Journal of Theoretical and Applied Information Technology, 102(19). [25]