AI FOR PREDICTING STUDENT MENTAL HEALTH CRISES: A DATA-DRIVEN APPROACH FOR EARLY INTERVENTION

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INTRODUCTION. The rise of mental health crises among students is gradually becoming a menace globally because it does not just affect academic performance but also deep-seated social and personal implications [1;2;3], hence the necessity for innovative solutions. According to the World Health Organization, approximately 20% of teenagers and young adults tend to experience mental health challenges (with a greater portion left undiagnosed or untreated) [10] due to a couple of reasons which includes academic pressure, financial concerns, social integration, and uncertainties as it concerns future employment. Conventional evaluation techniques like counsellor-to-student and self-disclosure; that depends on self-reported surveys and clinical evaluations, often fail to provide timely interventions.

Artificial intelligence (AI) technologies offer a promising solution to revolutionize mental health support by analysing diverse data sources, including health surveys, electronic records, and even social media activity, to anticipate crises before they escalate [4;5;6]. This study presents an AI-based predictive tool that is designed to specifically assess the risk of student mental health crises with the help of integrated data sources which includes behavioural, academic, and lifestyle indicators.

As this field continues to grow, there are ongoing research, and interdisciplinary collaborations that will be essential to refine predictive models and ensure the ethical deployment of AI technologies in mental health contexts. In the future, the research will focus on navigating regulatory challenges, enhancing international cooperation, and developing comprehensive training for educators and mental health professionals to maximize the benefits of AI in supporting student well-being [7;8;9].

METHODOLOGY

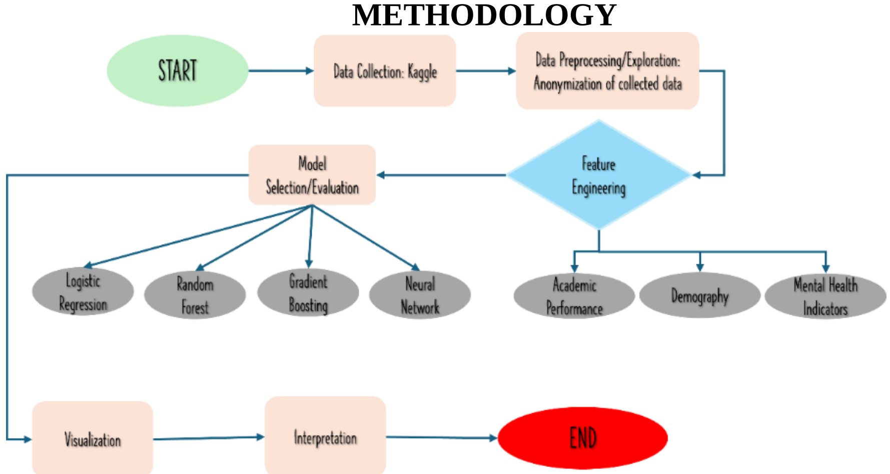

Figure 1. Research Procedure and Model Architecture

The study used different steps beginning with data collection from Kaggle with the title *"Student Mental Health"* which includes responses from over 100 university students on topics including academic stress, sleep patterns, and emotional well-being. The dataset comprises both numerical and textual responses on students' gender, academic performance, course of study, and mental health [11]. Fig.1 shows the different steps followed in this research. The dataset includes the following variables:

- **Demographics:** Gender, Age, Marital Status
- **Academic Profile:** Course, Year of Study, CGPA
- **Mental Health Indicatorss:** Self-reported Depression, Anxiety, Paniv Attacks

- **Utilization of Support Services:** Specialist Treatment Sought (Yes/No)

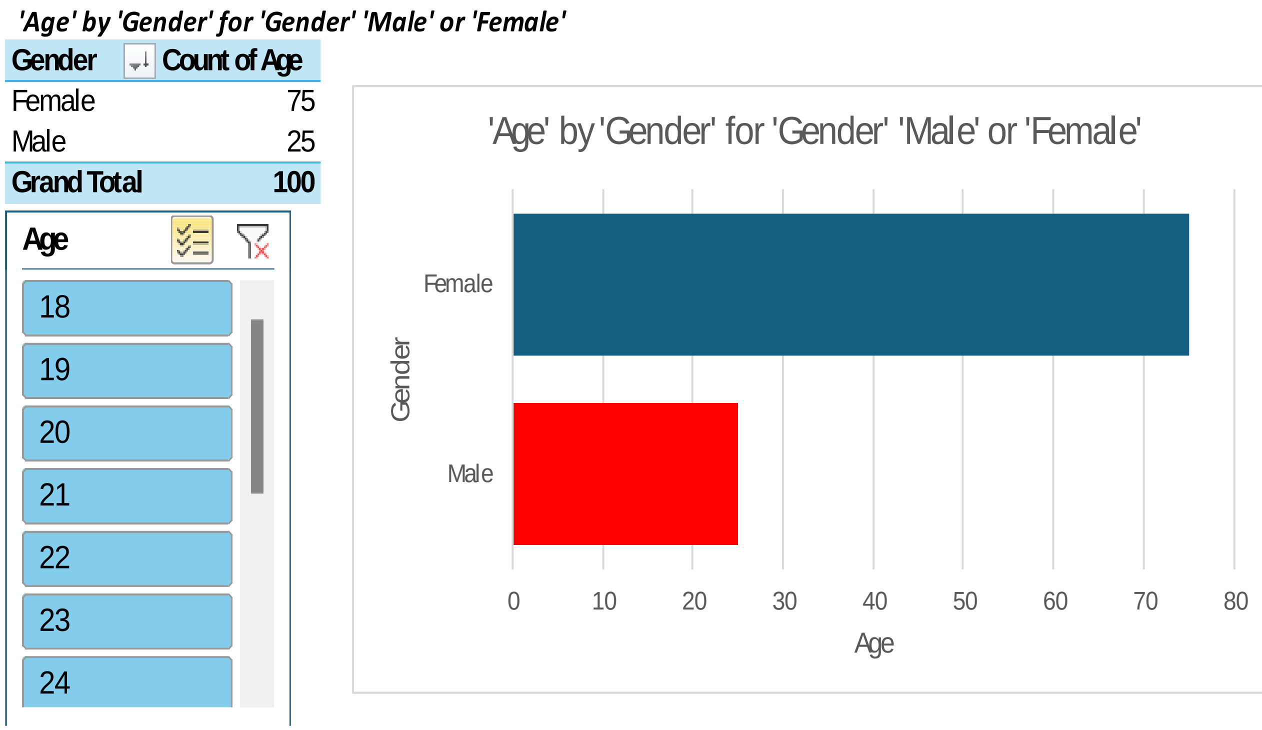

Figure 2. Age distribution of the students by Gender

Preprocessing (Data Cleaning)

After the data collection, the next step was *data cleaning*. Fig. 2 shows the distribution of gender by age after the data was cleaned using Pandas, with missing values removed.

Data Exploration

- **Prevalence:** Depression (≈30%), Anxiety (≈35%), Panic Attacks (≈20%).
- **Help-Seeking:** <10% of symptomatic students accessed specialist care.
- **Academic Correlates:** Lower CGPA (<3.0) is modestly associated with increased mental health symptoms.
- **Demographic Patterns:** Female students and those in transitional academic years (first and final year) exhibit higher rates of distress.

AI METHODOLOGIES FOR PREDICTING MENTAL HEALTH RISK

Model Selection

- **Logistic Regression:** This is most suitable for binary classification because of its high level of interpretability. A *recall* of **1.00** for *class 0 (absence of mental health condition),* On the other hand, the *recall* on *class 1* was low at **0.12** (*presence of mental health condition)***,** while the F1-Score for *class1* was **0.22** and an overall accuracy of **0.67.**

- **Random Forests:** This combines many decision trees to improve predictive accuracy and reduce the risk of overfitting. An *accuracy* of **71%,** with a *recall* of **1.00** for *class 0* and **0.25** for *class 1,* and an *F1-Score* of **0.40** for *class 1*; indicating that it fails to identify a significant number of actual positives.

- **Gradient Boosting:** It combines multiple decision trees in a sequence, with each tree correcting errors made by its predecessor. It shows an *F1-Score* of **0.50** for *class 1,* with the overall *accuracy* of **0.71**. The recall for class 0 and class 1 were **0.92** and **0.38** respectively.

- **Neural Networks:** This is a very powerful model for large and complex data, but because of the limited amount of dataset used in this research, it achieved a of **0.00** for *recall* and *F1-Score* in *class 1*.

Model	Precision (0)	Recall (0)	F1-Score (0)	Support (0)	Precision (1)	Recall (1)	F1-Score (1)	Support (1)	Accuracy	Macro Avg. F1	Weighted Avg. F1
Logistic Regression (LR)	0.65	1.00	0.79	13	1.00	0.12	0.22	8	0.67	0.51	0.57
Random Forest (RF)	0.68	1.00	0.81	13	1.00	0.25	0.40	8	0.71	0.61	0.66
Gradient Boosting (GB)	0.71	0.92	0.80	13	0.75	0.38	0.50	8	0.71	0.65	0.69
Neural Network (NN)	0.62	1.00	0.76	13	0.00	0.00	0.08	8	0.62	0.38	0.47

Table 1. Model Performance

Feature Engineering

This process involves selecting, modifying, and creating new features from raw data, hence improving the ability of the model to capture patterns. From the above model(s) selection, we saw that there were struggles particularly in *class 1- indicating the presence of mental health issues.*

Key Features and Their Importance

Academic Performance Metrics:

- **CGPA/Year of Study:** These quantitative indicators of students can correlate with stress and mental health. It is transformed from a range (e.g., “3.00 - 3.49”) into a numerical average, where a *High CGPA* could mean *lower mental health issues.*

Demographic Information:

- **Age, Gender, Marital Status:** Categorizing the ages can give deeper insights on the mental state of students e.g. 18-22, 23-25. Likewise, we encoded gender as a numerical value(s) [0 for Female, 1for Male] and their marital status.

Mental Health Indicators:

- **Depression, Anxiety, Panic-Attack:** These are binary indicators of students’ mental status which are converted to numerical values (1 for Yes, 0 for No); these can be analysed using demographic and academic variables.

Implementation of Feature Engineering

To enhance the model selection using feature engineering, we wrote down some codes in python after installing the necessary libraries like pandas (to access the dataset-.csv), matplotlib (visualization) and seaborn (conversion).

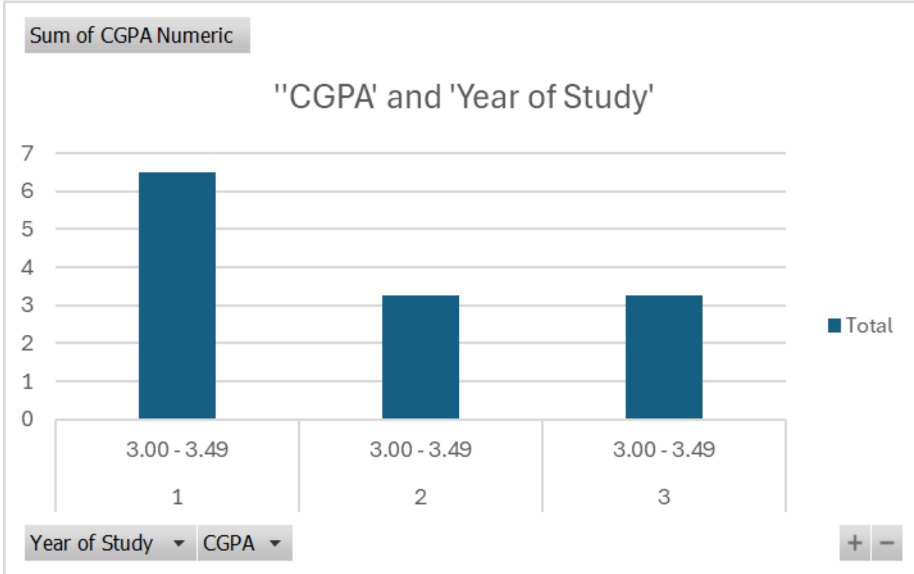

Figure 3. Comparing CGPA and Year of Study

Insights From the Datasets

Class Imbalance and Model Performance: After the analysing the dataset, it was observed that the models show varying performance between *class 0* and *class 1*. To illustrate, whereas all models got higher *recall* for *class 0* (non-mental health issues), they still struggled with *class 1* (mental health issues) especially in the low *precision* and *recall* for *class 1* in models like Neural Network scoring 0.00 for both metrics.

Best Performance: Gradient Boosting from the model demonstrates to be the best balance with an *F1-score* of 80% and *class 0* of 50% for *class 1*. This implies that it has the capacity to capture more complexities in data in comparison to others.

Impact of Academic Performance: As seen in the chart above (Fig.3), the presence of mental health issues among students is closely related to the different stages or levels of learning due to more academic pressures.

Need for Targeted Interventions: Having seen how demographic factors and academic performance can greatly influence mental health, it is advisable that universities should consider implementing targeted mental health initiatives focusing on specific courses, age groups and year of study.

DISCUSSION

Summary of Key Findings: In this research, Gradient Boosting was the best performing model with an *F1-score* of 80% for *class 0* and 50% *class 1*. This means that it can balance precision and recall effectively. It also suggests the importance of academic achievement as a possible predictor of mental health status. This finding corresponds with existing literature that emphasizes academic stress as a significant factor in mental health issues among the student population [12;13].

Mental Health Policy and Practice Implications

The ability to identify early warning signs of mental health issues through predictive modelling can facilitate early intervention, which can potentially minimize the severity of crises. Schools could use such knowledge to develop tailored mental health support services for specific disciplines or courses of study. For instance, students with low GPAs might have to be provided with additional counselling and academic support, wherein their academic performance and psychological well-being are addressed simultaneously. By identifying at-risk groups, educational authorities can cautiously distribute mental health resources better, with support services being delivered where they are most required [14].

Ethical Considerations and Limitations

Imbalance in Class Distribution: The large imbalance in class distribution found in the dataset implies that future studies must be aimed at ways to improve model performance on the minority class possibly using SMOTE [15].

Privacy Issues: Institutions need to ensure that they are following ethical standards and data protection regulations [16].

Human Oversight: The use of artificial intelligence to forecast mental health outcomes underscores the need for human intervention in the decision-making process. Clinical judgment should always have a primary role in assessing the suitability of any intervention based on AI predictions.

Real-World Implementations and Strategies for Intervention

Early Warning Systems: Educational institutions can develop artificial intelligence-powered early warning systems that alert mental health professionals when students exhibit signs of distress for effective clinical responses.

Integration with Support Services: Artificial intelligence models can be integrated into existing student support systems, enabling the early identification of students who may need additional resources.

Targeted Awareness Initiatives: Data derived from predictive models can guide the creation of tailored mental health awareness initiatives for specific demographic populations or academic schools.

Opt-in Monitoring Programs: Institutions can provide opt-in monitoring for students who have a history of mental health problems with users' consent.

Improved Clinical Evaluation: Mental health practitioners may utilize artificial intelligence results to improve clinical assessments, thereby gaining a better insight into student well-being.

CONCLUSION: The study demonstrates the promise of machine learning models in identifying problems with students' mental health. Our research, considering demographic factors, leads also to important variables influencing academic success; this makes it possible to envision quite an early and effective intervention in mental health. The ethical concerns and challenges raised in the present work, however, make evident the need for scrupulous implementation and ongoing research. Balancing artificial intelligence's prediction potential and student confidentiality individual cases would be essential in crisis and mental health intervention.

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THE USE OF ESPERANTO IN THE DEVELOPMENT OF METALANGUAGE AWARENESS

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Summary: The article examines the features of the grammatical structure and syntax of Esperanto, its importance in psycholinguistics, as well as its role in the theory of universal language. The article considers the use of Esperanto in educational where it promotes the development of metalanguage skills and facilitates the development of other languages.

Key words: linguistic theories, assimilation, era of globalization, medium, educational interaction.

Esperanto is an artificial language created at the end of the 19th century by the Polish linguist Ludwik Zamenhof. Despite the fact that this language did not become a global means of communication, as originally planned, it had a significant impact on the development of linguistics, as well as on world linguistic culture. In this article, we will look at how Esperanto influences language learning, the development of linguistic theories and techniques, as well as its cultural and educational role [1].

Initially, Esperanto was conceived as a universal language that could serve as an international means of communication, promoting peace and mutual understanding between peoples.

However, even if this ideal has not been fully achieved, Esperanto has become an important object for linguistic research. One of the key features of Esperanto is its constructivism: the language was designed with maximum logic and simplicity in mind. Grammatical structure and syntax in Esperanto offers unique opportunities for exploring language structures. Its grammar contains no exceptions, which makes its study less difficult compared to natural languages. Esperanto has a fairly simple morphology, as well as a unified system of declensions and conjugations. This provides linguists with a convenient tool to study the interaction of different language elements such as roots, prefixes, and suffixes, as well as their role in the formation of new words [6].

Some researches in the field of psycholinguistics also actively uses Esperanto to understand how people perceive and assimilate language structures. Esperanto can serve as an ideal material for experiments, as its simplicity and regularity allow us to explore cognitive processes such as the perception of grammatical errors or the speed of language acquisition. Esperanto in the context of the theory of universal language Esperanto continues to play an important role in discussions about the possibility of creating a universal language.[2].

Linguists such as Noam Chomsky and his followers have considered hypotheses about the existence of a universal grammar that could underlie all human languages. Esperanto, with its regular grammar and universal elements, serves as an interesting example of an artificially created language that could embody the principles of universality. Esperanto also provides an opportunity to explore the concepts of "linguistic universalism" and "linguistic relativity." Languages designed to be neutral