Mental Health Survey Dashboard: An AI-Driven Early Risk Detection and Well-Being Analytics System for Student Communities

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***Abstract*— Over the past couple of years mental health issues among the students have been growing out of proportions in respect to the pressure of academic life, social demands, and change in lifestyles. Mental health survey is a common practice in universities where they understand the well-being of students but through the traditional survey the university ends up receiving a high level of report that is not dynamic and that might not reflect timely intervention. This constraint minimizes the capacity by the institutions to detect the stress trends at an early stage and offer sufficient support. To resolve this problem this study introduces a Mental Health Survey Dashboard, which is a data-driven program to be presented as a tool to achieve this aim through the analysis and visualization of mental health data among students using a meaningful and interactive approach. The system gathers responses to surveys regarding stress, anxiety, sleeping habits, and students' academic workload, and uses predictive analytics and AI-based risk detection to determine students or groups which might be at risk. The dashboard delivers insights in form of dynamically displayed visuals, trend analysis, and alerts that can help an institution to learn more about mental health trends among the student body. The offered system will facilitate better awareness of mental health and encourage timely interventions in the educational setting by allowing early warning indicators of stress and supporting informed decision-making.**

Keywords*— *AI-based risk detection, data visualization, interactive dashboard, mental health analytics, mental health survey, predictive stress analysis, student well-being, survey data analysis.

I. Introduction

During recent years, the mental health issue among college students has reached its peak because of the pressure of studying, social life requirements, economic needs, and the hasty lifestyle transformation. Stress, anxiety, depression, and emotional exhaustion are some of the factors that are evident among many students in academics, thus, affecting the academic performance and well-being of the students. Other causes of student psychological distress are the high competition, test anxiety and deprivation of adequate rest, as well as, adapting to new academic systems. Moreover, mental health problems in a higher education campus are also enhanced by social isolation, excessive use of the digital-based world, and ambiguity about future career opportunities.[1], [2], [3]

Schools have seen the need to measure the student mental health and usually carry out surveys and questionnaires to determine the levels of stress, anxiety, and emotional state of being. Such surveys serve the purpose of gathering information about the psychological condition of a student and assist universities know the level of mental health complications in their student groups.[4], [5] Nevertheless, the conventional method of the survey in most cases results in the creation of inactive reports or summary statistics that only allow making slight conclusions on the intricate process of student mental health. These reports are frequently not demonstrated in time and can be developed after a long time period that does not enable institutions to trace mental health trends and reveal the newly appeared problems in a timely manner.

The inability of current methods to generate actionable insights based on the survey data is also another shortcoming of this set of methods. In most situations, the gathered data is not fully harnessed since it is not incorporated in analytic systems that facilitate dynamic visualization or computerized detection of risks. The administrators and counselors will struggle to determine when to pay attention to which groups of people are at a high risk or when the stress levels of patients have all of a sudden risen, during the critical academic moments like the examination or project submission.[6] Consequently, there will be missed opportunities by the institutions to offer early support and intervention to the students who require them most.

In a bid to tackle the challenges, data-driven systems are increasingly required that could convert raw survey responses to useful outputs that could be used to make proactive decisions. Interactive dashboards and predictive analytics will be an efficient method of visualizing mental health trends, finding patterns between various student's groups, and tracking the changes over time. These systems might assist these institutions to gain a deeper insight into the causes of stress, and allow them to develop specific awareness campaigns, counseling services, and wellness programs.[7]

Key Contributions:

- Creation of an AI-driven mental health risk predictor model to understand survey data and determine the possible levels of stress and anxiety in students.
- Creating an interactive dashboard that presents the data of the survey on mental health in the form of dynamic charts and trends.
- Introduction of an early-warning system that is capable of identifying the emerging stress patterns within the communities of students.
- Implementation of a privacy-focused mental health analytics model to guarantee confidential and legitimate approach to sensitive information on students.

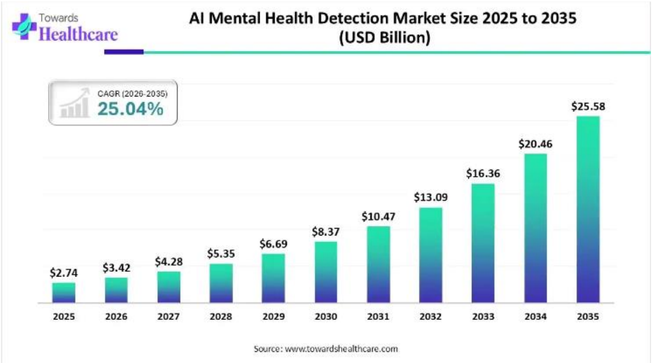

Fig 1: AI Mental Health Detection Market Size 2025-2035[8]

II. LITERATURE REVIEW

A. Mental Health Surveillance in Educational Institutions.

Mental health surveillance in schools has been receiving growing popularity in consideration with the increased rate of stress, anxiety, and depression amongst the learners. Universities and colleges have started several programs like counseling programs, mental health programs and surveys on psychological assessments to determine the emotional health of their students. Other institutions use regular mental health tests carried out to determine general tendencies in the levels of stress experienced by students through online or paper surveys. Such tests assist the administrators and the counselors to get acquainted with the most frequent difficulties that the students may experience such as school stress, loneliness, and disproportionate lifestyle.[9], [10], [11] Although such efforts are supportive and have a role to play in awareness, they usually are based on manual analysis or on the state of reporting that narrows down the response of any institution to arise mental health issues.[12]

B. Survey-Based Mental Health Analysis

Analysis by survey is among the most distinct methods applied in the evaluation of the mental health status concerning student populations. Symptoms of depression and anxiety are measured by means of the standardized questionnaires namely the Patient Health Questionnaire (PHQ-9) and the Generalized Anxiety Disorder Scale (GAD-7). All these validated instruments enable researcher and institutions to record meaningful information on psychological well-being and also to detect an individual with moderate or serious symptoms of mental health. Besides these standardized instruments, universities can also come up with specialized stress and anxiety surveys which are customized to certain student groups.[13] The effectiveness of these surveys is still questionable even though they offer important information on mental health issues due to the delay in analysis and the unavailability of the automated systems to conduct the continuous monitoring.[14], [15]

C. Healthcare Analytics Data Visualization.

Data visualization is an important component of healthcare analytics that helps to convert the complex datasets into visual data that can be easily interpreted. Dashboards, charts, and graphical interfaces allow healthcare professionals and administrators to easily detect trends, patterns and anomalies in big data. Visualization tools can be utilized in the context of mental health monitoring to assist the institution to monitor the stress patterns in various groups of students, how the trend changes over time during academic cycles, and how effective the mental health programs are. Interactive dashboards will deliver an active environment that enables users to filter, explore, and analyze data in real-time to enable decision-makers to respond better to developing mental health problems in schools.[16], [17], [18]

D. Mental Health Prediction with the Help of Machine Learning.

The current developments in machine learning and artificial intelligence have brought in more opportunities in clinical predictive models of mental health conditions based on survey and behavioral indicators. Logistic regression, support machine learning, decision trees and neural networks belong to machine learning models that have been extensively applied in identifying early symptoms of depression, anxiety and psychological distress.[19], [20] These models examine different aspects such as lifestyle practices, sleeping, academic stress and emotional reaction in order to determine patterns that relate to mental health risks. With the help of prediction analytics, the institutions will have an opportunity to identify the vulnerable people earlier and offer them specific interventions to decrease the probability of developing serious mental health issues.[21], [22]

E. Research Gap

- The majority of existing systems of mental health survey do not give dynamic or real time information but only generate the static reports.
- Existing solutions tend to be not real-time, and it is hard to keep track of the trends in student mental health in real-time.
- Several systems lack predictive machine learning models to help in detecting students that are susceptible to stress, anxiety or depression.
- The interactive dashboard use is not substantial and allows administrators and counselors to see and navigate mental health data in an effective manner.
- The available solutions can hardly create early-warning indicators that inform institutions that there is some pattern of stress among the students.

- A lot of mental health monitoring systems do not include decision-support tools that can assist universities in designing specific wellness programs or interventions.
- The traditional systems do not address privacy and ethical issues associated with managing sensitive mental health data as well as they should.

III. Methodology

A. *Dataset Description*

The initial phase of the proposed system is gathering the mental health-related data of the students by filling online surveys. Such surveys are aimed at identifying many psychological and lifestyle variables that determine the state of the student. The responses obtained are the main data to be analyzed and predicted in the Mental Health Survey Dashboard.

Table I:
Dataset Description

Parameter	**Description**
Dataset Source	Primary data collected through an online student mental health survey
Data Collection Method	Online questionnaire using Google Forms or custom survey web application
Target Population	University students
Dataset Size	Approximately 200–500 student responses (depending on survey participation)
Number of Attributes	10–12 attributes related to mental health and lifestyle factors
Data Type	Mixed data types including numerical and categorical variables
Time Period of Collection	Data collected over a period of 2–4 weeks
Data Privacy	All responses anonymized to protect student identity
Target Variable	Mental health risk level (Low Risk, Moderate Risk, High Risk)
Dataset Usage	Used for visualization, statistical analysis, and machine learning prediction

B. *Data Preprocessing*

After receiving the survey data, the raw data is preprocessed in order to enhance data quality and reliability. The step will guarantee that the dataset is clean, consistent, and could be used in further analysis and machine learning modeling. Preprocessing aids in the elimination of noise and standardization of responses in order to derive some meaningful insights.

Preprocessing involves key steps:

- Cleaning of values which are missing or incomplete.
- Removing duplicate entries
- Normalizing survey scores
- Assessing the levels of stress in pre-defined classes.

C. *Feature Engineering*

The process of feature engineering is identifying and transforming valuable variables in the survey data that can effectively describe the state of the mental health of the students. These characteristics will assist machine learning models to earmark associations amongst the lifestyle variables and the levels of psychological stress. The meaningful features chosen enhance the prediction precision and allow taking mental health trends further.

The main characteristics obtained in the survey data are the following:

- Sleep quality
- Academic workload
- Social support level
- Lifestyle habits
- Screen time usage

D. *Machine Learning Model*

Several machine learning algorithms are employed to determine the level of mental health risk of the students based on the resulting processed data. These models are observing the patterns on the survey answer and categorizes students into various mental health risk groups. The purpose of the model is to recognize students, who might need early help or assistance.

The models of machine learning applied:

- Logistic Regression
- Random Forest
- Support Vector Machine
- Gradient Boosting
- Prediction objective:
- Low Risk
- Moderate Risk
- High Risk

E. *Dashboard Development*

Mental Health Survey Dashboard is a tool that is intended to outline survey findings and predictive outcomes with interactive images. The dashboard would allow administrators, counselors and researchers to track the mental health patterns, and patterns associated with risks and analyze student well-being among various groups. A responsive interface and user-friendly interface are created with the help of modern web technologies.

Technologies used for development:

Frontend

- React.js or Angular

Backend

- Python (Flask / Django) or Node.js

Data Visualization Tools

- Tableau
- Power BI
- Plotly or D3.js

F. *Dashboard Features*

Mental Health Survey Dashboard offers a control board within an interactive environment that allows one to observe mental health trends among students and forecast them using data visualization and predictive analytics. It allows institutions to see the patterns of stress, identify high-risk students, and make reasonable decisions on mental wellness programs.

1) *Current Mental Health Trends in Real-Time*

The dashboard uses real-time mental health indicators as calculated by responses to the surveys. It shows the description of the stress levels and it works out an overall index of anxiety among different groups of students and it will enable the institutions in understanding the overall mental health of the student population.

2) Risk Detection Alerts

A case detection system is an automated system that is used to detect high levels of stress or anxiety among students. The dashboard gives timely support and intervention based on machine learning predictions of people or groups at high risk so that they can be supported and intervened.

3) Demographic Analysis

The dashboard offers the insights about the differences in mental health conditions among varied sets of students as well as among the students belonging to various student demographic groups such as:

- Gender
- Course or academic program
- Academic year

4) Time-Based Analysis

This option monitors the fluctuations in stress levels over time and shows a difference in the stress levels during the most important academic events like examinations, project deadlines, or submission of work.

5) Recommendation System

The system proposes proper interventions involving mental wellness plans on the basis of any stress pattern patterns identified such as counseling sessions, relaxation activities and mental health awareness workshops.

G. Implementation

The suggested system can be described as a web-based platform that involves survey data collection, analysis and visualization based on machine learning. The architecture of the system is broken down into a frontend interface that provides analytics, a backend server to process and integrate data with the models, and a database to store the responses to the survey and the prediction results.

Tools and Technologies

Frontend

- React.js
- HTML/CSS
- Bootstrap

Backend

- Node.js / Python Flask

Database

- MongoDB / MySQL

Machine Learning Tools

- Python
- Scikit-learn
- TensorFlow

IV. PROPOSED SYSTEM

A. Novel Contribution

- Incorporation of AI-based mental health risk predictors to determine at-risk students based on survey data through the use of surveys.
- Creation of a stress trends and mental wellness indicators interactive mental health analytics dashboard which displays in real-time.
- Introduction of an early-warning system where high-risk students or groups which are identified by predictive analysis are automatically detected.
- Demographic and time-related analysis to determine the trends of stress among gender, courses, years of study and examination.
- Introduction of a recommendation module that proposes interventions like counseling sessions, relaxation and wellness programmes.
- Integration of privacy-sensitive data management such as anonymization and safe package of sensitive mental health data.

Fig 2: System architecture of the proposed Mental Health Survey Dashboard from data collection to risk prediction and visualization.

B. System Architecture

Data Collection Layer:

- Responses are received by the online mental health surveys provided by students.
- The information encompasses the stress levels, signs of anxiety, sleeps, academic pressure, and social factors.

Data Preprocessing Layer

- Clusters values with missing or illegal values.
- census scores the survey and sets them into analysis.

Feature Processing Layer

- Extracts important characteristics, including sleeping quality, education load, social support, and screen time.

Machine Learning Layer

- Implemented models include Logistic Regression, Random Forest, SVM and Gradient Boosting.
- Ethnographic forecasts student levels of Mental health risk (Low, Moderate, High).

Database Layer

- Stores question survey, processed information and prediction results safely.
- The system is implemented in MongoDB or MySQL.

Graphic presentation and Dash Board Layer.

- Presents information in the form of charts, graphs and analysis of trends.
- Gives administrators and counselors a chance to track the development of mental health patterns.

Anti-Intrusion Software Layer.

- Produces early-warning notifications on the high-risk students.
- Recommends some of the interventions like counseling sessions and wellness programs.

V. RESULTS

A. Model Performance

The machine learning models that were referred to in the study to predict the level of mental health risk in students are assessed with the help of standard classification metrics. These indicators are Accuracy, Precision, Recall, and F1 Score, which are used to determine the effectiveness of the models in terms of their ability to classify the students as various risk level students. There are several algorithms that were experimented with to determine the best suited model in forecasting risk of developing mental health using survey data.

TABLE II:Model Performance Comparison

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Logistic Regression	0.84	0.83	0.82	0.82
Random Forest	0.91	0.90	0.89	0.89
Support Vector Machine	0.88	0.87	0.86	0.86
Gradient Boosting	0.92	0.91	0.90	0.90

Based on the findings of the experiment, the Gradient Boosting model worked better in predicting the level of mental health risks compared to the results of the Randome Forest model, which came in second. These findings represent a sign that ensemble-based machine learning approaches are more effective in the complex pattern detection in mental health survey data.

B. Dashboard Evaluation

The Mental Health Survey Dashboard was tested by using the feedback provided by students and administrative users with regard to its usability and effectiveness. The respondents played around with the dashboard, where they were able to view visualization about the trend of stress, demographic interpretation, and risk detection alerts.

The results of the feedback showed that the dashboard was useful in enhancing the awareness of the mental health patterns among students. According to administrators and counselors, the interactive visualizations helped with flagging high-risk groups and comprehending the variation in the level of stress during the various academic crunch time. The system was also helpful to the students in their ability to become aware of factors that affect their mental well-being. In general, the review indicated that the dashboard is an effective and convenient instrument to track the mental health of students.

C. Discussion

Through the outcomes of this experiment, it is possible to state that machine learning can be efficiently applied to analyzing the data collected in the Mental Health Survey and that it can assist in identifying the group of students who might be under the threat of high stress or anxiety levels. Ensemble-based models, including Gradient Boosting and Random Forest, were found to be more accurate in their predictions compared to other models because they were able to provide nonlinear relationships between psychological conditions and lifestyle factors.

Predictive analytics, which is then incorporated into an interactive dashboard, also make the system more useful. The dashboard enables the institutions to understand the well-being of students better because it enables them to visualize mental health trends among various groups of students and within various academic years. There is also the early-warning alert mechanism that facilitates proactive interventions whereby counselors and administrators can react fast in case of any mental health concern.

VI. FUTURE SCOPE

To add to the system, future studies may incorporate real-time sources of data, e.g., wearable health devices or mobile apps, to measure both behavioral and physiological signs of stress. To enhance the predictive models, it is also possible to apply the advanced deep learning algorithms and larger datasets to enhance the accuracy of prediction. As well, the system might include a chatbot-based mental health support, which is based on AI resources and enables students to get access to guidance or resources right away. Increasing the size of the dashboard with customized wellness advice and combining it with the services of university counselors may enhance the efficiency of mental health monitoring and intervention programs even more.

VII. CONCLUSION

In this study, a Mental Health Survey Dashboard was introduced, allowing to track and evaluate the mental health of students based on the data of the surveys and the results of the machine learning and intuitive visualizations. The proposed system would turn the old-fashioned mental health survey into an analytical tool based on data that will give significant insights into stress levels, anxiety, and other psychological issues that influence the students. The predictive analytics system extends real-time visualization through dashboards and, therefore, allows institutions to identify high-risk individuals or groups and act proactively. The experimental outcomes prove that machine learning models may be used to effectively predict the risk level of mental health and the dashboard interface facilitates access and interpretation of mental health trends. Altogether, the suggested framework will facilitate the creation of awareness regarding mental wellness and help the educational institutions to establish proactive steps that would enhance the well-being of the student body.

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