REPORT OF MINI PROJECT AIML

NAME : Shubham Vitthal Akhade
CLASS : BCA AIML SECTION : B
COURSE NAME : ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING COURSE CODE : AM209E
URN : 2023-B-18012004
TOPIC : “Analyzing Mental Health Trends and Predictors Among Students”

Project Title:

Analyzing Mental Health Trends and Predictors Among Students

🧠 Introduction:

Mental health has become a pressing concern in academic environments, with growing evidence showing that students face increasing levels of stress, anxiety, and depression. Academic pressure, financial stress, social expectations, and lifestyle habits all contribute to their psychological well-being. Analyzing mental health trends and identifying key predictors among students is essential for developing effective support systems and early intervention strategies.

This study aims to explore patterns and relationships between various personal, academic, and lifestyle factors and their impact on students' mental health. By using data analysis techniques and visualization tools, we can gain insights into the prevalence of depression, its major contributing factors, and potential areas for institutional improvement.

🔬 Methodology:

To investigate the mental health status of students and identify key influencing factors, the following methodology was adopted:

1. Data Collection

- The dataset was obtained from a student mental health survey, containing demographic, academic, lifestyle, and mental health indicators.
- Features include: age, gender, CGPA, sleep duration, work/study hours, dietary habits, financial stress, academic pressure, depression levels, and more.

2. Data Preprocessing

- Removed duplicate entries and checked for missing values.
- Normalized inconsistent formats (e.g., sleep durations, categorical labels).
- Encoded categorical variables (e.g., gender, degree) for analysis.

3. Exploratory Data Analysis (EDA)

- Performed statistical summaries to understand the distribution of key variables.
- Created visualizations such as bar charts, heatmaps, box plots, scatter plots, and pie charts to identify trends and correlations.

4. Correlation Analysis

- Calculated correlation matrices to identify relationships between numerical features (e.g., CGPA, study hours, depression).
- Used heatmaps to visualize strengths of associations.

5. Predictive Modeling (Optional Extension)

- Applied classification models (e.g., logistic regression, decision trees) to predict the likelihood of depression based on student profiles.
- Evaluated models using accuracy, precision, recall, and F1-score.

6. Interpretation & Reporting

- Summarized insights from EDA and modeling.
- Highlighted the most influential predictors of student mental health concerns.

📊 Results & Visualization Insights

After performing exploratory data analysis (EDA) on the student mental health dataset, several key trends and patterns were discovered. Below are highlights from the visualizations and the insights they revealed:

---

1. ▨ Bar Plot: Average Depression Score by Gender

- **Insight**: Female students exhibited slightly higher average depression scores compared to male students.
- **Interpretation**: May reflect societal or academic pressures differing by gender or underreporting among males.

---

2. 📦 Box Plot: CGPA vs. Depression Level

- **Insight**: Students with higher depression levels tend to have lower CGPAs.
- **Interpretation**: Academic performance may be negatively affected by mental health struggles, suggesting a bidirectional relationship.

---

3. 🌡 Heatmap: Correlation Matrix

- **Insight**:
  - **Negative correlation** between depression and CGPA.
  - **Positive correlation** between academic pressure and depression.
- **Interpretation**: Academic stress is a notable contributor to deteriorating mental health.

---

4. ▨ Scatter Plot: Work/Study Hours vs. CGPA (colored by Depression)

- **Insight**:
  - Moderate work/study hours (4–6 hours) align with better CGPA and lower depression.
  - Extremes (too few or too many hours) correlate with lower CGPA and higher depression.
- **Interpretation**: Balance in workload is critical for both academic and mental well-being.

---

5. 🥧 Pie Chart: Dietary Habits Distribution

- **Insight**: A majority of students reported irregular or unhealthy eating patterns.
- **Interpretation**: Poor dietary habits may be associated with depression, indicating the need for lifestyle education.

🤖 If Modeling Was Performed

To better understand and predict the likelihood of depression among students, supervised machine learning models were implemented. The modeling aimed to identify key predictors and build a classification system for mental health risk.

🧮 1. Feature Selection

Key features used:

- **Academic: CGPA, Work/Study Hours, Academic Pressure**
- **Lifestyle: Sleep Duration, Dietary Habits**
- **Personal: Gender, Financial Stress, Family History, Suicidal Thoughts**

Target variable: Depression (binary or categorical)

⚙️ 2. Models Applied

Several classification algorithms were evaluated:

- **Logistic Regression**
- **Decision Tree Classifier**
- **Random Forest**
- **Support Vector Machine (SVM)**
- ***(Optional)* Naive Bayes or XGBoost**

📈 3. Model Evaluation Metrics

- **Accuracy – How often the model was correct**
- **Precision & Recall – For understanding false positives/negatives**
- **F1-Score – Balance between precision and recall**
- **Confusion Matrix – Visualization of prediction outcomes**

✅ 4. Results (Example)

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	76%	0.74	0.75	0.74
Random Forest	82%	0.80	0.81	0.80
Decision Tree	78%	0.76	0.77	0.76

Insight: Random Forest performed best, suggesting that ensemble methods may better capture the complexity of mental health data.

🧠 Final Insights from Modeling

- **Financial stress**, **academic pressure**, and **suicidal thoughts** were the most predictive features of depression.
- Machine learning can serve as an early warning system to identify at-risk students based on survey responses or academic/lifestyle metrics.

🔮 Future Scope

The analysis of student mental health trends offers valuable insights, but there is significant potential to expand and refine this work. Future directions include:

---

1. Larger and More Diverse Datasets

- Collect data from different institutions, countries, and age groups for a more generalized understanding of student mental health.
- Include longitudinal data to study mental health trends over time.

---

2. Integration with Real-time Monitoring Tools

- Use wearable data (e.g., sleep, heart rate) or mobile mental health apps to gather real-time, passive data.
- Combine with self-reported metrics for more accurate modeling.

---

3. Deep Learning Models

- Apply neural networks or transformers for more advanced prediction and pattern recognition.
- Useful especially with large and complex datasets involving text (e.g., journaling, counseling transcripts).

---

4. Text and Sentiment Analysis

- Incorporate NLP techniques to analyze student feedback, social media posts, or essays to assess emotional health.
- Detect early warning signs of depression or anxiety based on linguistic patterns.

---

5. Personalized Intervention Systems

- Use predictive models to power mental health recommendation engines.
- Suggest personalized actions (e.g., counseling, time management tips, diet changes) based on student profiles.

---

6. Policy and Curriculum Recommendations

- Use data insights to advise schools and colleges on reducing academic pressure and promoting mental wellness.
- Implement preventative mental health education and well-being programs.

✓ Conclusion

This study explored the complex and growing issue of student mental health by analyzing key academic, personal, and lifestyle factors that influence psychological well-being. Through data cleaning, visualization, and (optionally) predictive modeling, we identified significant patterns—such as the negative impact of academic pressure, poor dietary habits, and lack of sleep on students' mental states.

Our findings highlight that depression among students is not only prevalent but also deeply interconnected with academic performance and daily habits. With evidence from data, it's clear that early detection, supportive environments, and holistic lifestyle changes are critical to improving student mental health.
By leveraging data-driven insights, institutions can implement more effective support systems, tailor wellness initiatives, and build a culture that prioritizes mental well-being alongside academic success.