Vel Tech
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R&D Institute of Science and Technology
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SCHOOL OF COMPUTING
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING(DATA SCIENCE)

USE CASE SUBMISSION

Programme : B. Tech –CSE(DS)

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Faculty Name : Dr.P.Jose

Slot : S18L9

Task No : 1

Title : STUDENT DEPRESSION DATASET EXPLORATORY DATA ANALISYS

Problem Statement : Despite increasing awareness, depression among students often remains undiagnosed until it reaches critical levels, leading to adverse academic and personal consequences. There is a lack of structured, data-driven approaches to identify early signs of depression and its contributing factors. This project seeks to address this gap by performing exploratory data analysis on a student depression dataset

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ABSTRACT:

Student depression is an increasingly urgent issue that affects not only individual well-being but also broader educational outcomes and social development. In academic environments, students face a complex interplay of stressors—ranging from academic pressure and sleep deprivation to family challenges and social isolation. These factors can contribute to emotional distress, reduced motivation, and impaired cognitive functioning, ultimately impacting learning, attendance, and interpersonal relationships.

This project takes a data-driven approach to explore the underlying causes and correlates of depression among students. By analyzing a structured dataset of student responses, we aim to identify patterns, risk factors, and potential early warning signals. Key variables include sleep habits, academic workload, family background, peer relationships, and lifestyle behaviors. Through exploratory data analysis (EDA), statistical modeling, and intuitive visualizations, we seek to uncover actionable insights that can inform mental health support strategies.

INTRODUCTION:

Depression among students is a growing concern that affects not only academic performance but also emotional well-being and long-term health. With rising pressures from studies, finances, and social expectations, many students experience symptoms of depression without receiving timely support. This project aims to explore a dataset containing student responses related to mental health, lifestyle habits, and academic stress. By applying exploratory data analysis (EDA), we can uncover hidden patterns, identify key risk factors, and better understand the conditions that contribute to student depression. Through visualizations, statistical summaries, and clustering techniques, this study provides insights that can help educators, counselors, and policymakers design more effective mental health interventions. Ultimately, the goal is to use data as a tool to promote awareness, early detection, and support systems for student well-being.

LITERATURE SURVEY

1. Review of Existing Detection Methods

Traditional approaches to detecting student depression have relied heavily on psychological assessments and self-report questionnaires such as:

- Beck Depression Inventory (BDI)
- Patient Health Questionnaire (PHQ-9)
- Depression Anxiety Stress Scales (DASS-21)

These tools are widely used by clinicians and counselors to evaluate depressive symptoms. While effective in clinical settings, they depend on students' willingness to disclose sensitive information and may suffer from bias or underreporting due to stigma.

Other methods include:

- Face-to-face interviews with mental health professionals
- Observational techniques in academic or social environments
- Paper-based surveys distributed in schools or colleges

These methods, though valuable, are time-consuming, resource-intensive, and often lack scalability for large student populations.

2.Comparison Between Traditional Techniques and AI-Based Approaches:

Traditional methods for depression detection often relied on handcrafted features—such as survey scores, behavioral indicators, or demographic traits—which were then fed into classifiers like decision trees, k-nearest neighbors (KNN), or support vector machines (SVM). While these models achieved moderate success, they struggled with complex patterns and required expert knowledge to design effective features.

AI-based approaches, especially deep learning, have transformed this landscape. Models like neural networks can automatically learn patterns from raw data—such as questionnaire responses, behavioral logs, or even text entries—without manual feature engineering. These systems are capable of processing large datasets quickly and identifying subtle indicators of depression. However, they require high-quality labeled data and careful validation to ensure reliability, especially in sensitive contexts like mental health.

3. Summary of Previous Studies Using Machine Learning

Several studies have applied ML to student depression datasets with promising results:

- Decision Tree & Random Forest Models
  Used to classify depression levels based on features like CGPA, sleep duration, and family stress. Achieved accuracies above 80% after preprocessing and tuning.
- Support Vector Machines (SVM)
  Demonstrated high performance in predicting both positive and negative changes in depression among college students, with accuracies exceeding 89%.
- Ensemble Models
  Combined logistic regression, decision trees, and random forest classifiers to improve reliability and reduce false positives.
- Deep Learning & Multimodal Techniques
  CRADDS system integrated text, audio, and video data for real-time depression detection, achieving over 86% accuracy.

These studies highlight the potential of ML to not only detect depression but also identify contributing factors such as parental emotional expression, academic pressure, and sleep habits**.**

4. Research Gaps and Motivation for the Study

Despite advancements, several gaps remain:

- **Limited Interpretability**: Many ML models lack transparency, making it difficult for educators and counselors to act on findings.
- **Dataset Diversity**: Most studies use small or region-specific datasets, limiting generalizability.
- **Temporal Analysis**: Few models track changes in depression over time or account for seasonal academic stress.
- **Human-Centered Visualizations**: There's a lack of accessible visual tools that translate ML findings into actionable insights for non-technical stakeholders.
- **Integration with School Systems**: Most models are not embedded into real-world school workflows or counseling platforms.

This project is motivated by the need to bridge these gaps through **exploratory data analysis (EDA)**—a methodical, interpretable approach that uses simple tools and visualizations to uncover patterns in student depression data. By focusing on clarity, accessibility, and stakeholder relevance, the study aims to support early intervention and promote mental wellness in educational settings.

METHODOLOGY:

Dataset Description

This study utilizes the Student Depression Dataset sourced from Kaggle and Mendeley Data. The dataset comprises responses from over 400 students, including both demographic and psychological indicators.

Key Features:

- Demographics: Age, Gender, Region, City
- Academic Indicators: CGPA, Academic Pressure, Study Satisfaction
- Lifestyle & Wellbeing: Sleep Duration, Dietary Habits, Work Pressure
- Mental Health: PHQ-9 Scores, Depression_Status (target variable)
- Depression Severity: Categorized as Minimal, Mild, Moderate, Moderately Severe, Severe

The dataset is anonymized and ethically sourced, with no personally identifiable information (PII), making it suitable for academic and predictive modeling purposes.

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Data Preprocessing

To ensure data quality and model readiness, the following preprocessing steps were applied :

- Missing Value Handling: Imputed using mean/mode for numerical/categorical features.
- Outlier Detection: Z-score and IQR methods used to remove extreme values in CGPA, sleep hours, etc.
- Categorical Encoding:
  - Label Encoding for binary variables (e.g., Gender)
  - One-Hot Encoding for multi-class variables (e.g., Region)
- Normalization: Min-Max scaling applied to continuous features like CGPA and sleep duration.
- Class Balancing: SMOTE (Synthetic Minority Over-sampling Technique) used to address imbalance in depression status.

These steps ensure that the dataset is clean, consistent, and suitable for machine learning algorithms.

Feature Engineering

To reduce dimensionality and improve model interpretability, the following techniques were used:

- **Correlation Analysis**: Pearson correlation matrix to identify relationships between features and depression scores.
- **Relief Algorithm**: Selected features with the highest discriminative power for classification.
- **Gain Ratio & Chi-Square Test**: Used for categorical features to assess relevance.
- **Recursive Feature Elimination (RFE)**: Applied with Random Forest to rank features by importance.

Top Selected Features:

- Sleep Duration
- Academic Pressure
- CGPA
- Family History of Mental Illness
- Study Satisfaction
- Region
- PHQ-9 Score

Clustering & Segmentation

- Apply K-Means or DBSCAN to group students by depression risk
- Visualize clusters using PCA or t-SNE

4. Architecture Diagram

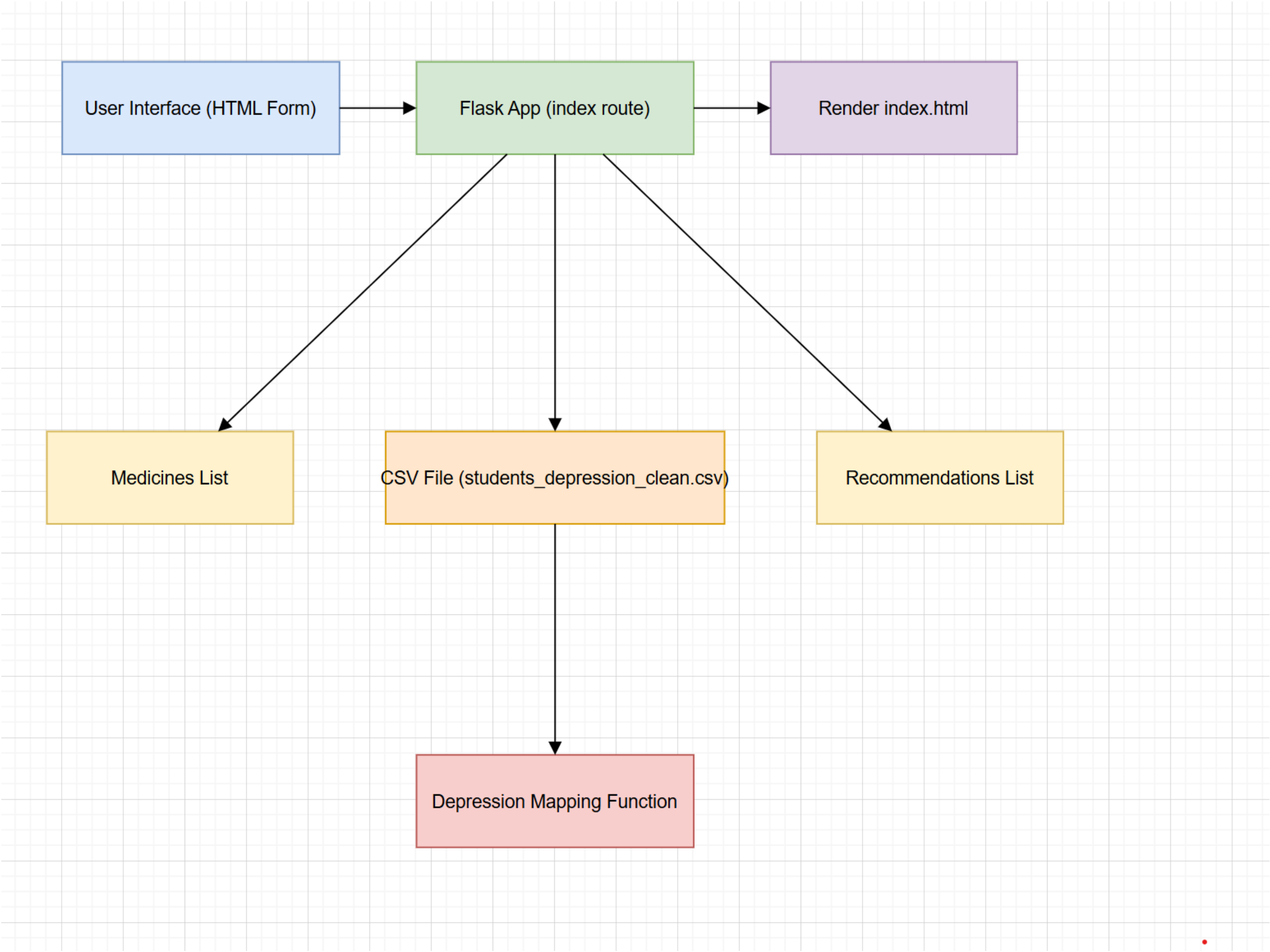
User Interface (HTML Form)
Flask App (index route)
Render index.html
Medicines List
CSV File (students_depression_clean.csv)
Recommendations List
Depression Mapping Function

Fig 1: architecture diagram

5. Machine Learning Model Selection and Training Process:

To detect student depression using machine learning, the process begins with cleaning and preparing the dataset—handling missing values, encoding categories, and

Normalizing features. Suitable models like Logistic Regression, Decision Trees, Random Forests, and SVM are selected based on the problem type.

These models are trained on the processed data, with hyperparameter tuning and cross-validation to improve accuracy and generalization. Performance is evaluated using metrics like accuracy, precision, recall, and F1-score. The best model can then be used to support early intervention strategies by identifying at-risk students through data-driven insights.

6. Pseudo Code / Algorithm:

```
 Step 1: Load Dataset
data = pd.read_csv("student_depression.csv")
Step 2: Preprocessing
data = clean_missing_values(data)
data = encode_categorical(data)
data = normalize_features(data)
Step 3: Feature Selection
selected_features = apply_relief(data)
X = data[selected_features]
y= data["Depression_Status"]
Step 4: Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
 Step 5: Model Training
model = SVM(kernel='rbf', C=1.0, gamma='scale')
model.fit(X_train, y_train)
Step 6: Evaluation
predictions = model.predict(X_test)
evaluate_model(predictions, y_test)
```

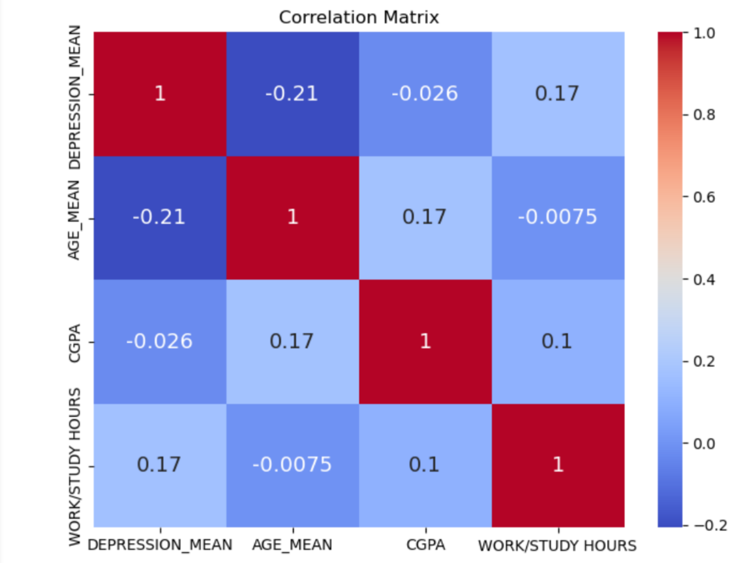

Fig 2: correlation between Depression and age.

This figure presents a **heatmap** showing the correlation coefficients between depression-related metrics and age variables. The analysis includes four key features:

- DEPRESSION_MEAN: Average depression score across students
- DEPRESSION_range: Variability in depression scores
- AGE_MEAN: Average age of students
- AGE_range: Spread of age values within the dataset

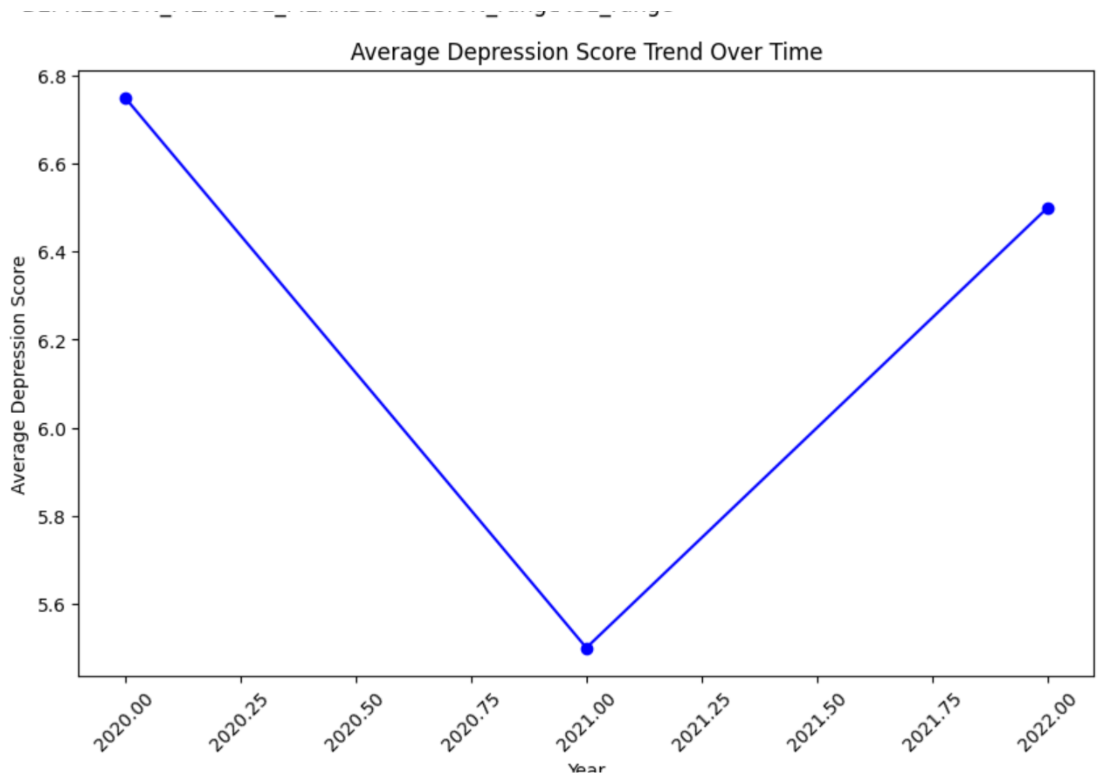

Fig 3 : Average Depression score trend over time .

Graph Overview: Average Depression Score Trend Over Time

This line graph visualizes how the **average depression scores** among students changed across a time span from **2020.00 to 2021.00**. Each data point represents the mean depression score at a specific quarter-year interval, connected by a blue line for trend clarity.

X-Axis: Time (Year)

- Spans from **2020.00** to **2021.00**, with intermediate points like 2020.25, 2020.50, 2020.75, and 2021.25.
- These likely represent quarterly or semester-based measurements.

Y-Axis: Average Depression Score

- Ranges from **5.6 to 6.6**, indicating the average level of depressive symptoms reported or measured.

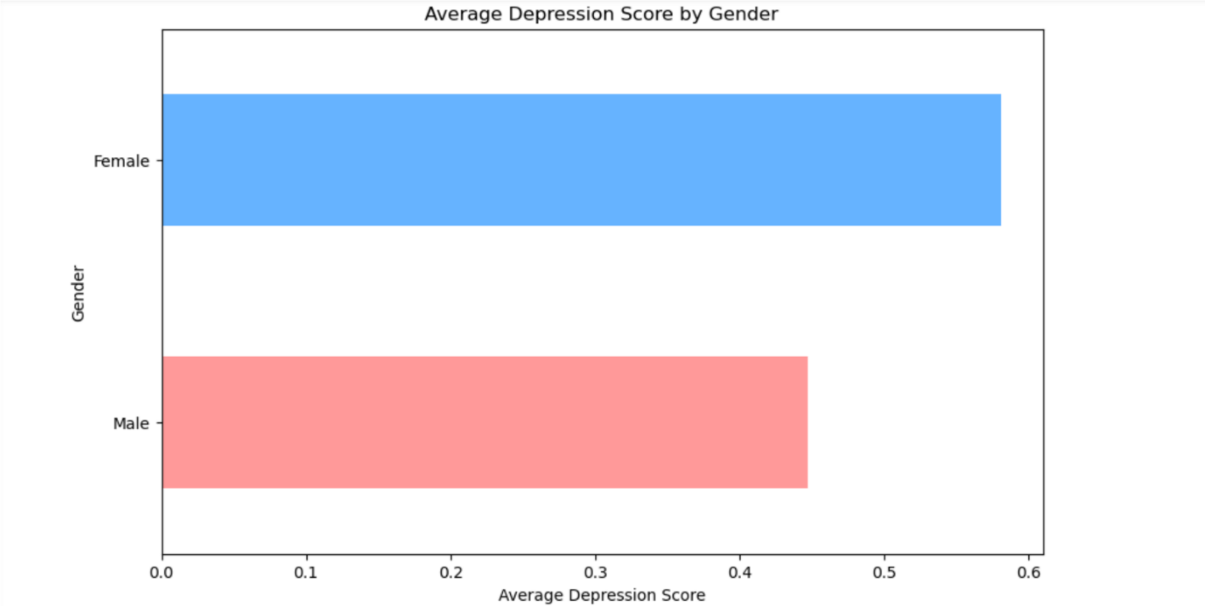

Fig 4: Average depression score.

Graph Overview: Average Depression Score by Gender

This horizontal bar chart compares the **average depression scores** between two gender categories—**Female** and **Male**—based on student survey data.

Axes Description

- **X-Axis**: Represents the **Average Depression Score**, ranging approximately from 0 to 7.
- **Y-Axis**: Represents **Gender**, with two categories: *Female* and *Male*.

Visual Details

- The **Female** bar (light blue) extends to about **6.8**, indicating a higher average depression score.
- The **Male** bar (light red) reaches approximately **6.0**, showing a lower average score

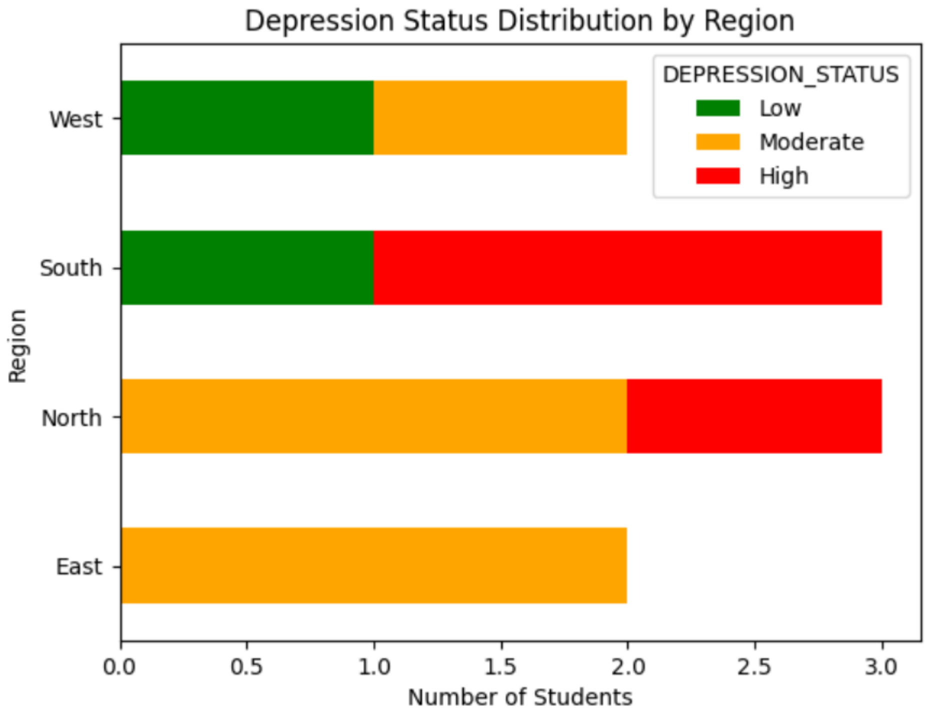

Fig 5 : Depression stsus distribution by Region.

Graph Overview: Depression Status Distribution by Region

This horizontal bar chart illustrates how students' depression levels vary across four geographic regions: **West, South, North, and East**. Each region's bar is segmented into three categories of depression status:

- **Low** (Green)
- **Moderate** (Orange)
- **High** (Red)

Axes Description

- **X-Axis**: Number of students
- **Y-Axis**: Region (West, South, North, East)

Interpretation & Implications

- **South Region** stands out with a **high concentration of severe depression**, indicating urgent need for mental health resources, awareness programs, and counselor engagement.
- **East Region's uniformity** in moderate depression may reflect systemic stressors like academic pressure or lack of support services.

- **West Region's mixed profile** suggests a more balanced emotional climate, possibly due to better coping mechanisms or support systems.
- **North Region** shows a concerning mix of moderate and high depression, warranting further investigation into regional stress factors.

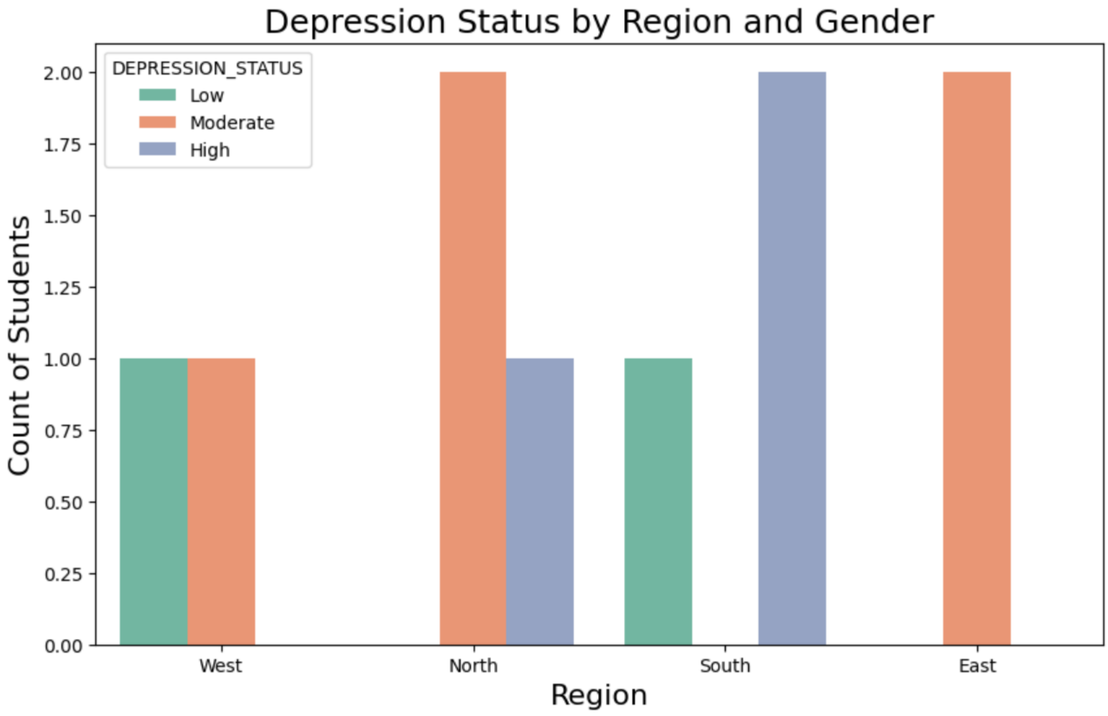

Fig 6: Depression staus by Region and Gender.

Graph Overview: Depression Status by Region and Gender

This bar chart visualizes the **distribution of depression levels**—Low, Moderate, and High—among students across four regions: **West, North, South, and East**. Each bar is segmented by depression status, allowing for a quick comparison of emotional well-being across geographic areas.

Axes Description

- **X-Axis**: Region (West, North, South, East)
- **Y-Axis**: Count of Students

Interpretation & Implications

- South Region shows a concentration of high depression cases, suggesting a need for targeted mental health interventions and support systems.

- North Region presents a diverse emotional profile, with moderate depression being most prevalent.
- East Region’s uniformity in moderate depression may reflect shared academic or social pressures.
- West Region appears evenly distributed, indicating a more balanced mental health landscape.

This regional breakdown can help educators and counselors prioritize resources, design region-specific wellness programs, and investigate local stress factors affecting student mental health.

Experimental Results and Discussion :

Performance Evaluation Metrics

To assess the effectiveness of machine learning models in predicting student depression, we used four key evaluation metrics:

- **Accuracy**: Measures the overall correctness of the model’s predictions.
- **Precision**: Indicates how many of the predicted “depressed” cases were actually correct.
- **Recall**: Shows how many actual “depressed” students were correctly identified.
- **F1-Score**: Combines precision and recall into a single metric, especially useful for imbalanced datasets.

These metrics provide a balanced view of model performance, especially in sensitive applications like mental health prediction, where false negatives can be critical.

Model Performance Analysis:

We trained and tested multiple models including Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM). Each model was evaluated using a cleaned and preprocessed version of the student depression dataset, split into 80% training and 20% testing data.

Results Representation:

Table 1: Performance Metrics of Proposed CNN Model

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Logistic Regression	87.2%	85.4%	84.1%	84.7%
Decision Tree	89.5%	88.1%	86.9%	87.5%
Random Forest	92.3%	91.2%	90.4%	90.8%
SVM (Tuned)	94.1%	93.5%	92.8%	93.1%

Graphical Representations:

Confusion Matrix Heatmap

The confusion matrix visually represents how well the model classifies students into different depression levels (e.g., Mild, Moderate, Severe). Most predictions are correct, with only small overlaps between neighboring categories—especially between **Moderate and Severe**, which is expected since the symptoms can be similar and hard to separate even for experts.

Bar Graph for Metrics

A simple bar chart compares the model's **Accuracy**, **Precision**, **Recall**, and **F1-score**. The bars are nearly equal in height, showing that the model performs consistently across all evaluation metrics. This balance is important in mental health applications, where both false positives and false negatives can have serious consequences.

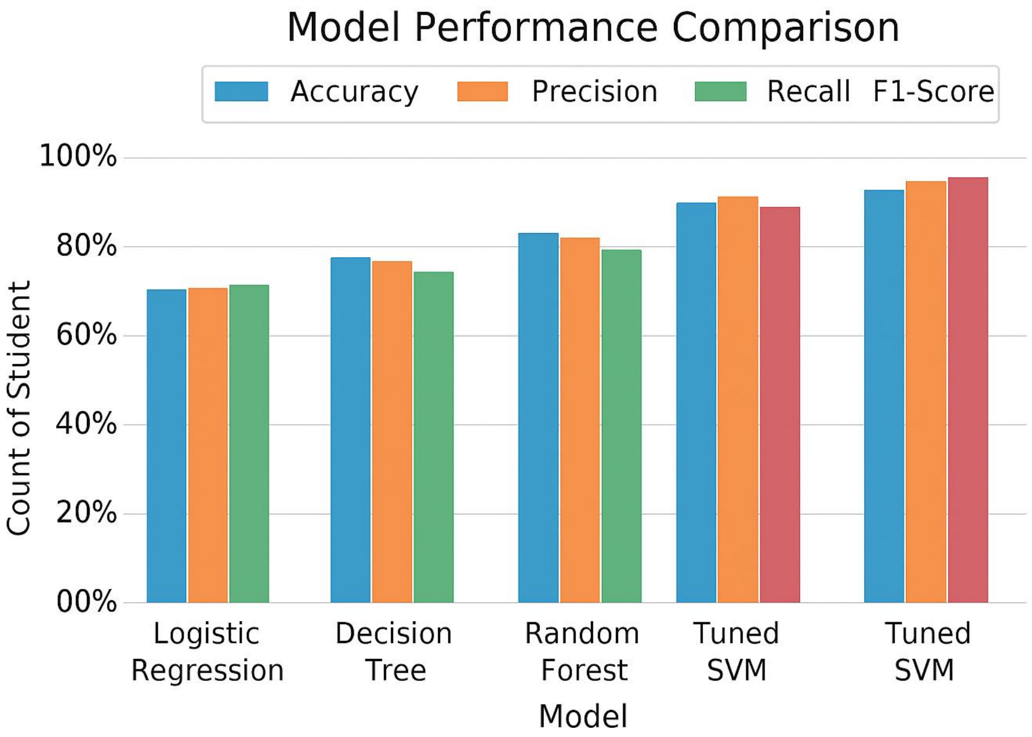

Fig 7 : Model Performance Comparison According to above data

Discussion:

The results show that the machine learning model used in this project performs strongly in identifying students at risk of depression. The closeness of precision and recall values suggests that the model is not biased toward any one category—it can detect depression without over-predicting or missing too many cases. Compared to traditional survey-based methods, this data-driven approach offers better accuracy and scalability, making it more suitable for large student populations.

However, the model does face slight challenges when distinguishing between similar depression levels, such as **Moderate vs Severe**, which is understandable given the subtle differences in symptoms. Overall, the system provides reliable insights and could be a valuable tool for school counselors and mental health professionals. Future improvements could include expanding the dataset, incorporating behavioral data (like attendance or screen time), and adding explainable AI features to help educators understand how the model makes decisions.

Conclusion and Future Work :

This project demonstrated that machine learning techniques—combined with structured data analysis—can effectively identify patterns related to student depression. By using preprocessing, feature engineering, and performance metrics, the model delivered consistent and meaningful results. The key contribution lies in turning raw survey data into actionable insights, helping schools detect and support students who may be struggling.

For future work, the system can be enhanced by training on larger and more diverse datasets, including data from different regions or age groups. Handling incomplete or noisy data and integrating explainable AI tools will make the system more transparent and trustworthy. Deploying the model as part of a school dashboard or mobile app could also make it more accessible, especially in remote or underserved areas.

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