# Predicting Student Depression Using Machine Learning :

## A Comparative Analysis

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# Introduction

## Why this subject?

- Student depression is a growing problem worldwide.
- It affects academic performance, social life, and overall well-being.
- Early detection is crucial for timely support and intervention.

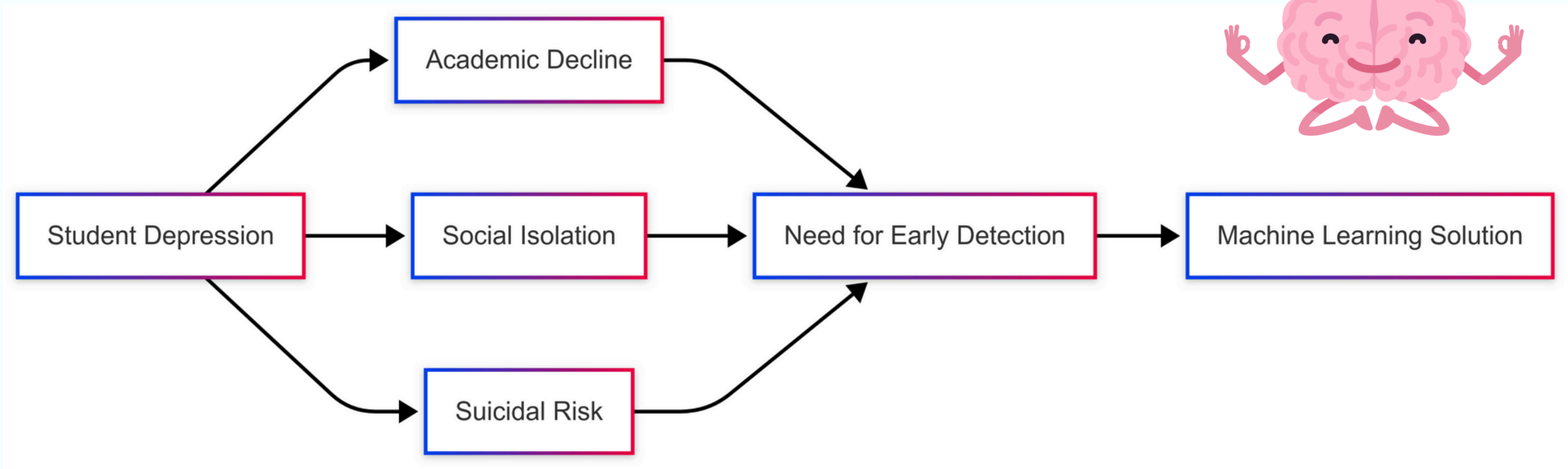
## Scientific Motivation

- Traditional detection methods are often subjective and slow.
- Data science and machine learning can help identify at-risk students more objectively and efficiently

# Introduction

## Project Objective

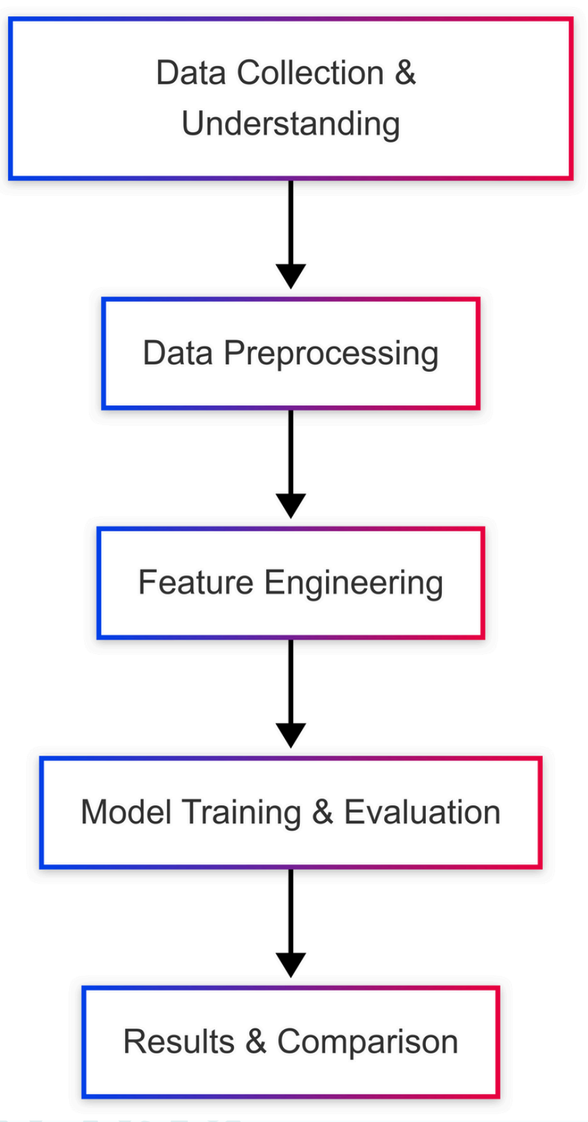
- **Build and evaluate predictive models to detect depression risk among students using real survey data.**



# Research Workflow Overview

- **Our scientific workflow followed these main steps:**

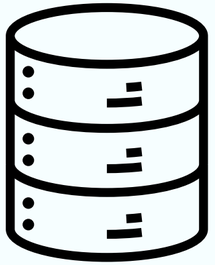
1. **Data Collection & Understanding**
2. **Data Preprocessing**
3. **Feature Engineering**
4. **Model Training & Evaluation**
5. **Results & Comparison**



# Data Collection & Understanding

## Dataset Overview

- **Source: Student depression survey dataset (27,901 records) from kaggle**
- **Each row = 1 student**
- **Features include:**
    1. **Age, Gender, City, Profession**
    2. **Academic Pressure, Work Pressure, CGPA (Academic performance)**
    3. **Study Satisfaction, Job Satisfaction**
    4. **Sleep Duration, Dietary Habits, Degree**
    5. **Suicidal Thoughts, Work/Study Hours, Financial Stress**
    6. **Family History of Mental Illness**
    7. **Target: Depression**



# Data Collection & Understanding

| | id | Gender | Age | City | Profession | Academic Pressure | Work Pressure | CGPA | Study Satisfaction | Job Satisfaction | Sleep Duration | Dietary Habits | Degree | Have you ever had suicidal thoughts ? | Work/ Study Hours | Financial Stress | Family History of Mental Illness | Depression |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | Male | 33.0 | Visakhapatnam | Student | 5.0 | 0.0 | 8.97 | 2.0 | 0.0 | '5-6 hours' | Healthy | B.Pharm | Yes | 3.0 | 1.0 | No | 1 |
| **1** | 8 | Female | 24.0 | Bangalore | Student | 2.0 | 0.0 | 5.90 | 5.0 | 0.0 | '5-6 hours' | Moderate | BSc | No | 3.0 | 2.0 | Yes | 0 |
| **2** | 26 | Male | 31.0 | Srinagar | Student | 3.0 | 0.0 | 7.03 | 5.0 | 0.0 | 'Less than 5 hours' | Healthy | BA | No | 9.0 | 1.0 | Yes | 0 |
| **3** | 30 | Female | 28.0 | Varanasi | Student | 3.0 | 0.0 | 5.59 | 2.0 | 0.0 | '7-8 hours' | Moderate | BCA | Yes | 4.0 | 5.0 | Yes | 1 |
| **4** | 32 | Female | 25.0 | Jaipur | Student | 4.0 | 0.0 | 8.13 | 3.0 | 0.0 | '5-6 hours' | Moderate | M.Tech | Yes | 1.0 | 1.0 | No | 0 |

# Data Collection & Understanding

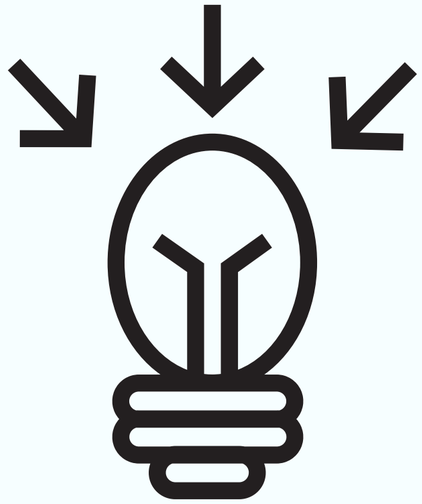
## Difficulties

- **Missing values and inconsistent formats (profession)**
- **Categorical variables (text, yes/no)**
- **Some irrelevant columns (ID, city)**

# Data Preprocessing

## Key Steps

- **Column Renaming: Standardized column names (lowercase, underscores, removed special characters).**
- **Cleaning: Removed extra quotes and whitespace from text fields.**
- **Categorical Mapping:**
  - **Converted sleep duration and yes/no answers to numbers.**
  - **Label encoded degrees, one-hot encoded dietary habits.**
- **Missing Values:**
  - **Replaced “?” with NaN.**
  - **Imputed missing numerical values with the median.**
- **Dropped Irrelevant Columns:**
  - **Removed ID, city, profession, and gender.**



# Data Preprocessing

```
RangeIndex: 27901 entries, 0 to 27900
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   age                    27901 non-null  float64
 1   academic_pressure      27901 non-null  float64
 2   work_pressure          27901 non-null  float64
 3   cgpa                   27901 non-null  float64
 4   study_satisfaction     27901 non-null  float64
 5   job_satisfaction       27901 non-null  float64
 6   sleep_duration         27901 non-null  int64  
 7   degree                 27901 non-null  int64  
 8   suicidal_thoughts      27901 non-null  int64  
 9   work/study_hours       27901 non-null  float64
 10  financial_stress       27901 non-null  float64
 11  illness_history        27901 non-null  int64  
 12  depression             27901 non-null  int64  
 13  diet_Moderate          27901 non-null  bool   
 14  diet_Others            27901 non-null  bool   
 15  diet_Unhealthy         27901 non-null  bool   
 16  academic_stress_combo  27901 non-null  float64
 17  burnout_index          27901 non-null  float64
 18  wellness_score         27901 non-null  float64
dtypes: bool(3), float64(11), int64(5)
memory usage: 3.5 MB
```

# Feature Engineering

## What we did

- Created new features to better capture student stress and wellness:
  - Academic Stress Combo: Academic Pressure × Financial Stress
  - Burnout Index: Academic Pressure × Work/Study Hours
  - Wellness Score: Study Satisfaction + Sleep Duration

## Scientific Rationale

- Combining related variables can reveal deeper patterns and improve model performance.
- These engineered features help quantify complex aspects of student life.

| | academic_stress_combo | burnout_index | wellness_score |
|---|---|---|---|
| 0 | 7.0 | 21.0 | 13 |
| 1 | 14.0 | 32.0 | 13 |
| 2 | 7.0 | 14.0 | 13 |
| 3 | 5.4 | 21.0 | 13 |
| 4 | 14.4 | 40.5 | 12 |

# Data Exploration & Correlation Analysis

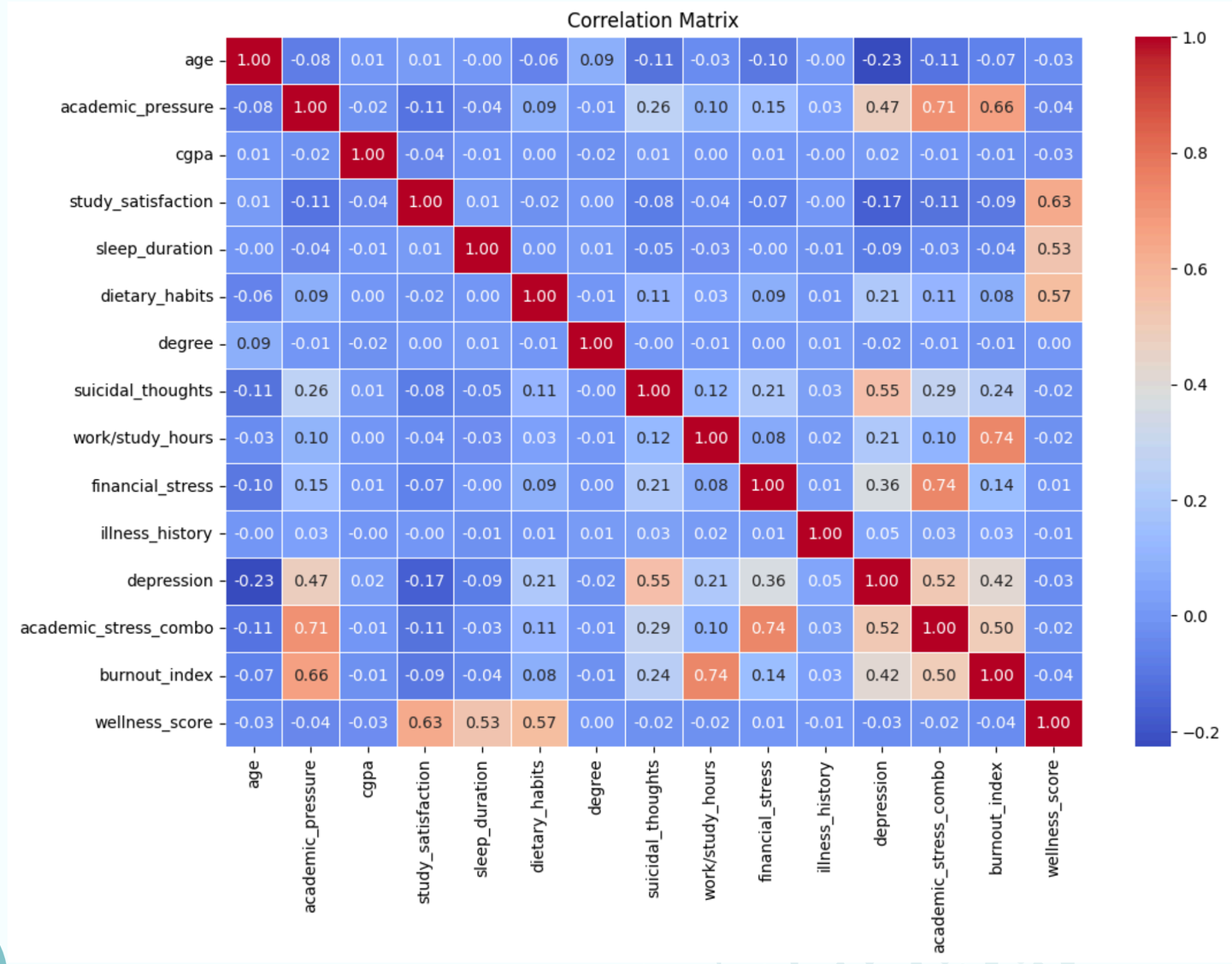
## What we did

- Explored relationships between variables using a correlation matrix.
- Identified which features are most strongly linked to depression.
- Used heatmaps for visual understanding of data structure.

## Scientific Rationale

- Correlation analysis helps in selecting the most relevant predictors for the model.
- For example, academic pressure, sleep duration, and financial stress showed strong correlations with depression.

# Data Exploration & Correlation Analysis



# Model Training

## Models Used

- Random Forest
- XGBoost
- Logistic Regression

## Scientific Rationale

- Data split into training and test sets (80/20, stratified for balance).
- Numerical features scaled for better model performance.
- Hyperparameter tuning with GridSearchCV and cross-validation for each model.
- Each model trained to predict depression risk.

# Model Evaluation

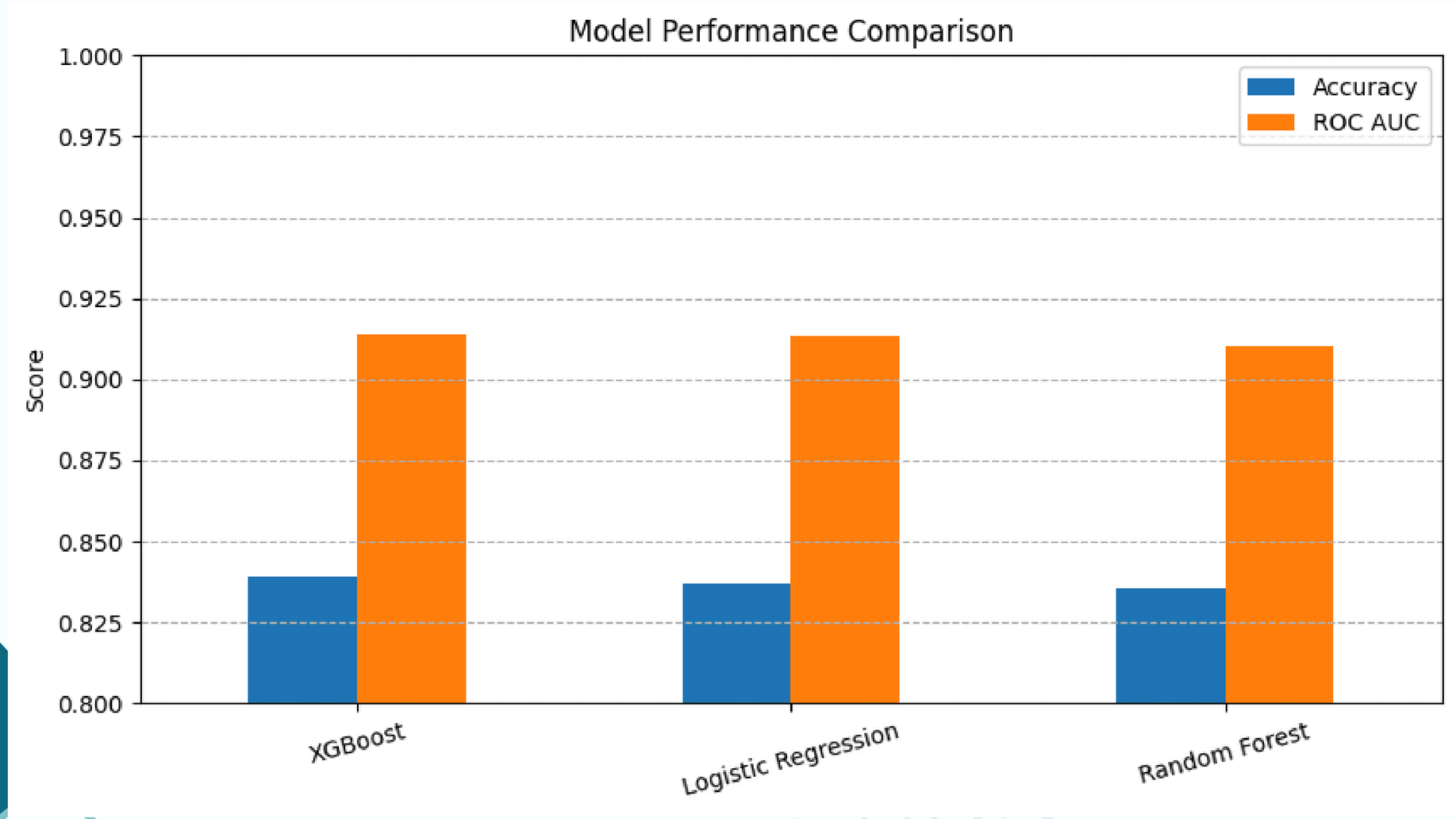
## How we evaluated the models

- **Metrics Used:**
  - **Accuracy**
  - **ROC AUC (Area Under the Curve)**
  - **Precision, Recall, F1-Score (from classification report)**
  - **Cross-validation scores for robustness**

## Scientific Rationale

- **Evaluated each model on the test set and with cross-validation to ensure results are reliable and not due to chance.**

# Model Evaluation



# Results Comparison

## Comparison of Model Performance

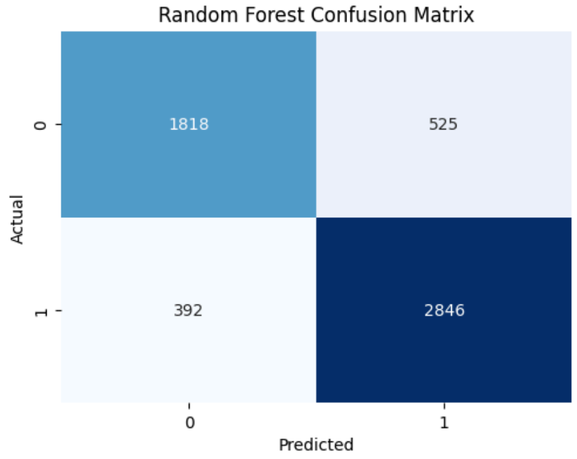
- Compared Random Forest, XGBoost, and Logistic Regression.
- Evaluated using:
  - Test Accuracy
  - Test AUC (Area Under Curve)
  - Mean Cross-Validation Accuracy
  - Mean Cross-Validation AUC

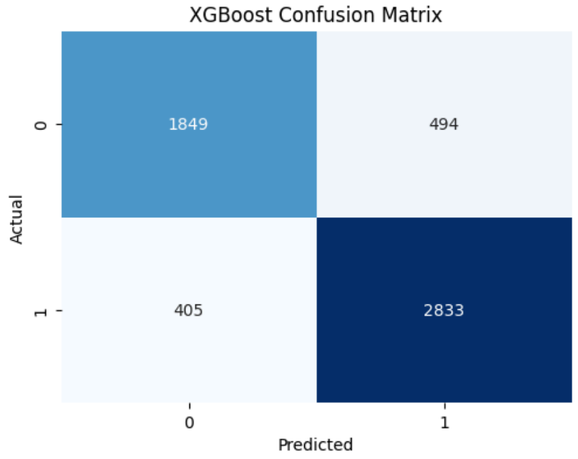
## Scientific Rationale

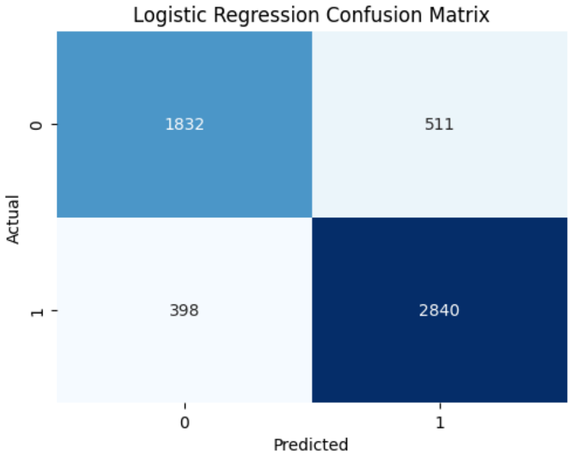
- XGBoost achieved the highest accuracy and AUC.
- Each model has strengths: Logistic Regression had higher precision, Random Forest better recall.

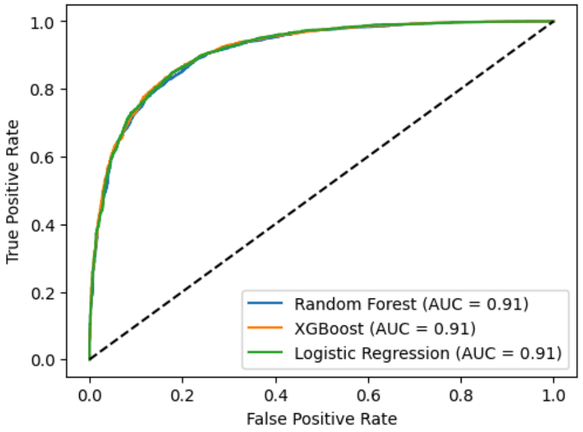
# Results Comparison

## Model Performance Benchmarks




Metrics Comparison

| Model | Accuracy | Precision | Recall | F1-Score | ROC AUC |
|---|---|---|---|---|---|
| Random Forest | 0.8357 | 0.8443 | 0.8789 | 0.8612 | 0.9103 |
| XGBoost | 0.8389 | 0.8515 | 0.8749 | 0.8631 | 0.914 |
| Logistic Regression | 0.8371 | 0.8475 | 0.8771 | 0.862 | 0.9136 |

# Challenges & Scientific Difficulties

## Data Quality Issues

- Missing values and inconsistent formats in the dataset
- Categorical variables with different representations (e.g., 'Yes', 'No', extra quotes)

## Modeling Challenges

- Class imbalance: fewer students with depression than without
- Avoiding overfitting while tuning models
- Choosing the right evaluation metrics for a fair comparison

# Scientific Impact & Future Work

## Scientific Contributions & Improvements

- **Improved Model Performance:**
  - **Achieved higher accuracy and AUC compared to basic models by:**
    - **Careful data cleaning and preprocessing**
    - **Feature engineering (stress combo, burnout index, wellness score)**
    - **Hyperparameter tuning and cross-validation**
- **Robust Evaluation:**
  - **Used mean cross-validation accuracy and AUC to ensure results are reliable and generalizable.**
- **Best Results:**
  - **XGBoost achieved the highest test accuracy and AUC.**
  - **All models showed improved mean CV accuracy and AUC after tuning.**

# Scientific Impact & Future Work

## Impact

- Demonstrates the value of machine learning for early depression detection in students.
- Provides a scientific workflow that can be reused or extended for similar mental health studies.

## Future Work

- Collect more diverse and larger datasets for better generalization.
- Explore advanced models (e.g., deep learning).
- Collaborate with mental health professionals for real-world deployment and validation.

# Conclusion

- **Machine learning can effectively predict depression risk among students using survey data.**
- **Careful data cleaning, feature engineering, and model tuning led to significant improvements in accuracy and reliability.**
- **XGBoost achieved the best results, but all models benefited from scientific workflow and robust evaluation.**

# References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# Thank You