

# Understanding and Predicting Depression to Enhance Mental Health Interventions

Group 8

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# Introduction



## Context

- Mental health, particularly depression, is a growing global concern. Understanding contributing factors is essential for creating effective interventions.
- Timely identification of at-risk individuals is crucial to providing support before the situation worsens.

# Introduction

## Current challenges

Many organizations struggle to predict depression using the available data, making it difficult to intervene proactively and prevent the escalation of mental health issues.

## Role of Depression Prediction

- Identify individuals at risk and prioritize support for them.
- Create targeted campaigns to raise awareness about key risk factors.
- Monitor and improve the effectiveness of mental health interventions based on data.

# Introduction

## Input

Individual characteristics: Personal details, Work/study status, Health and lifestyle, Psychological and financial factors, and Educational background.

## Output

Depression status prediction:

- Label 0: A person is predicted **not** to be depressed.
- Label 1: A person is predicted to be depressed.

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# Dataset

## Depression Survey/Dataset for Analysis

- The dataset was collected as part of a comprehensive survey designed to identify factors contributing to depression risk among adults.
- It was gathered through an anonymous survey conducted between January and June 2023, during a time when COVID-19 had significant impacts on mental health.

# Dataset

```
RangeIndex: 140700 entries, 0 to 140699
Data columns (total 20 columns):
 #   Column           Non-Null Count  Dtype  
 ---  --  
 0   id               140700 non-null   int64  
 1   Name              140700 non-null   object  
 2   Gender             140700 non-null   object  
 3   Age                140700 non-null   float64 
 4   City               140700 non-null   object  
 5   Working Professional or Student  140700 non-null   object  
 6   Profession         104070 non-null   object  
 7   Academic Pressure    27897 non-null   float64  
 8   Work Pressure        112782 non-null   float64  
 9   CGPA               27898 non-null   float64  
 10  Study Satisfaction   27897 non-null   float64  
 11  Job Satisfaction      112790 non-null   float64  
 12  Sleep Duration        140700 non-null   object  
 13  Dietary Habits        140696 non-null   object  
 14  Degree              140698 non-null   object  
 15  Have you ever had suicidal thoughts ? 140700 non-null   object  
 16  Work/Study Hours       140700 non-null   float64  
 17  Financial Stress        140696 non-null   float64  
 18  Family History of Mental Illness  140700 non-null   object  
 19  Depression            140700 non-null   int64  
dtypes: float64(8), int64(2), object(10)
memory usage: 21.5+ MB
```

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# Exploratory Data Analysis: Missing Values

id	0
Name	0
Gender	0
Age	0
City	0
Working Professional or Student	0
Profession	36630
Academic Pressure	112803
Work Pressure	27918
CGPA	112802
Study Satisfaction	112803
Job Satisfaction	27910
Sleep Duration	0
Dietary Habits	4
Degree	2
Have you ever had suicidal thoughts ?	0
Work/Study Hours	0
Financial Stress	4
Family History of Mental Illness	0
Depression	0

Figure: Missing values

# Exploratory Data Analysis: Target Distribution

- 0: Not depression.
- 1: Depression.

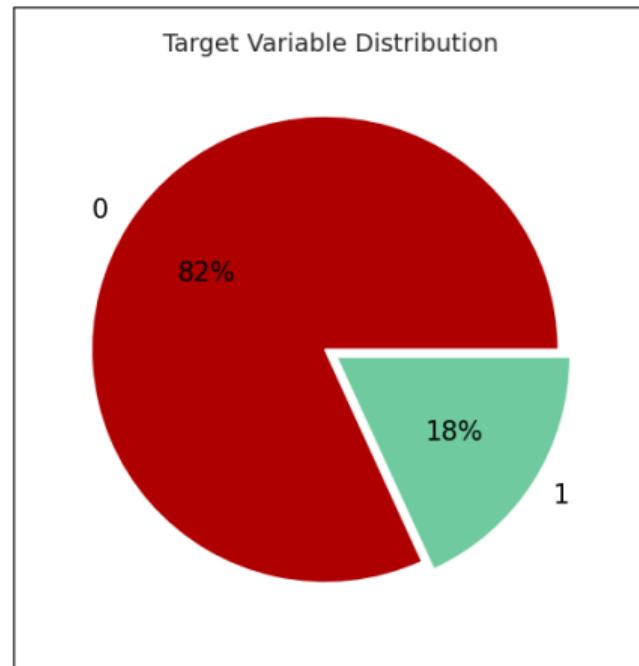
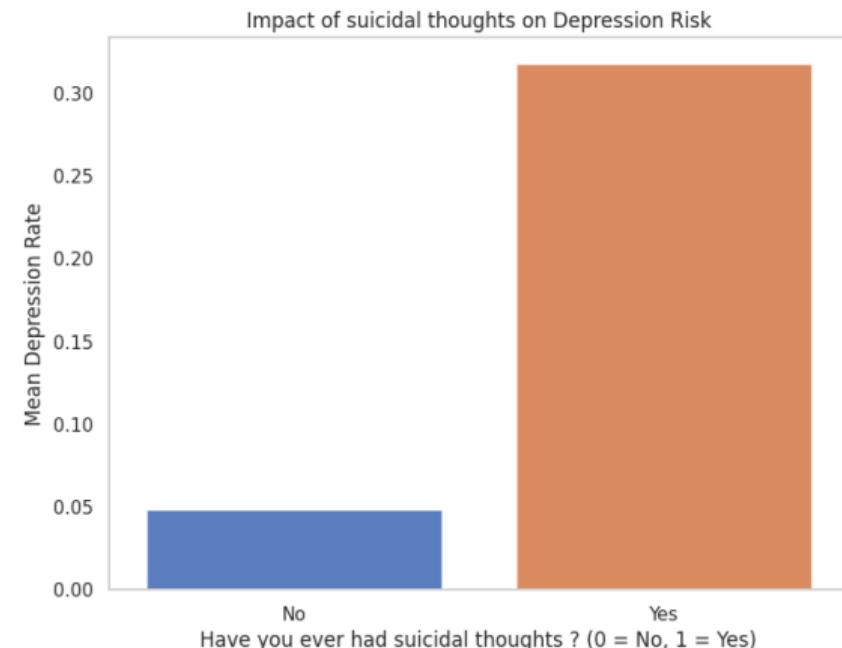
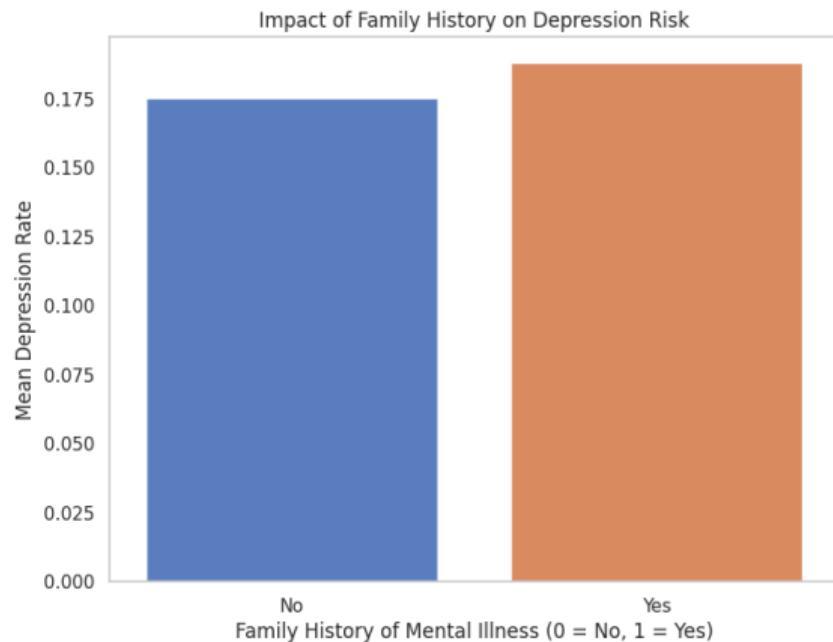
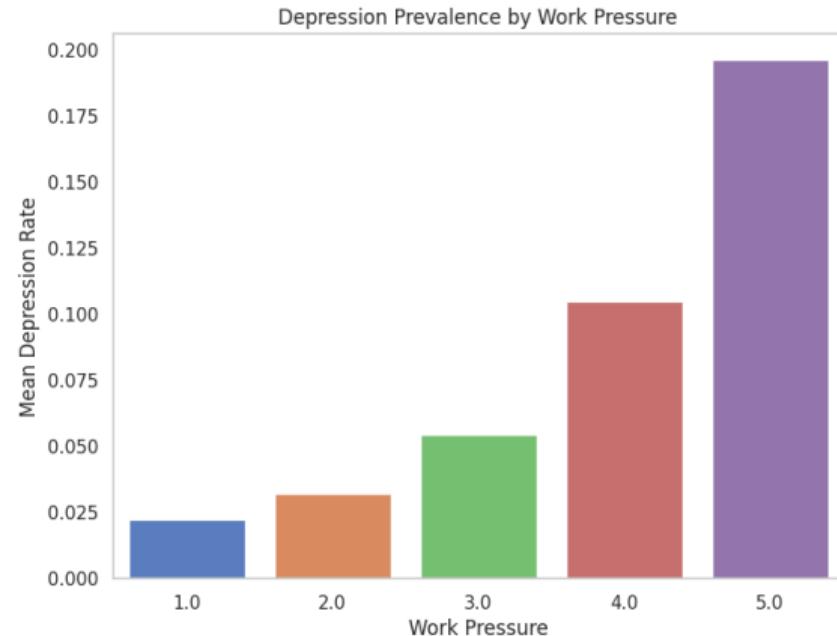
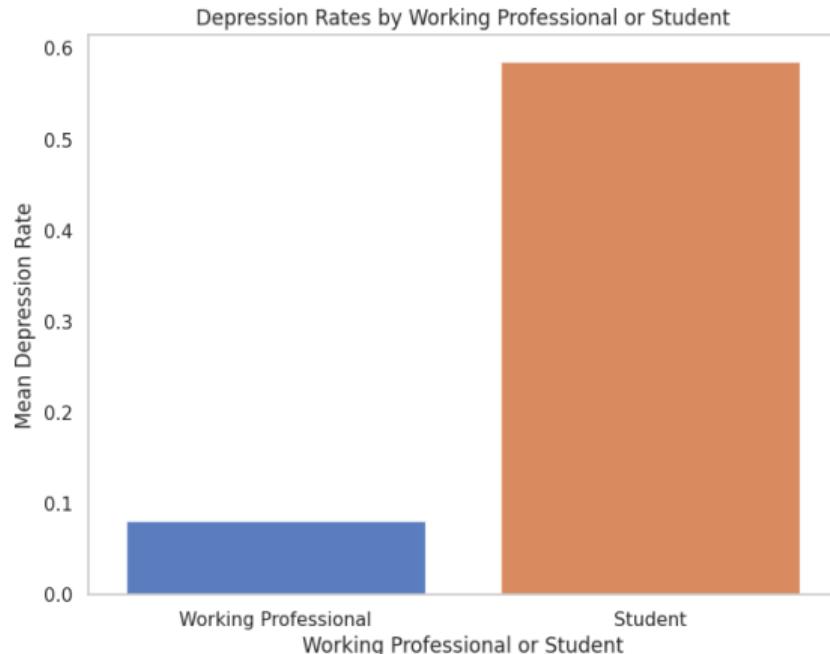


Figure: This is an example image.

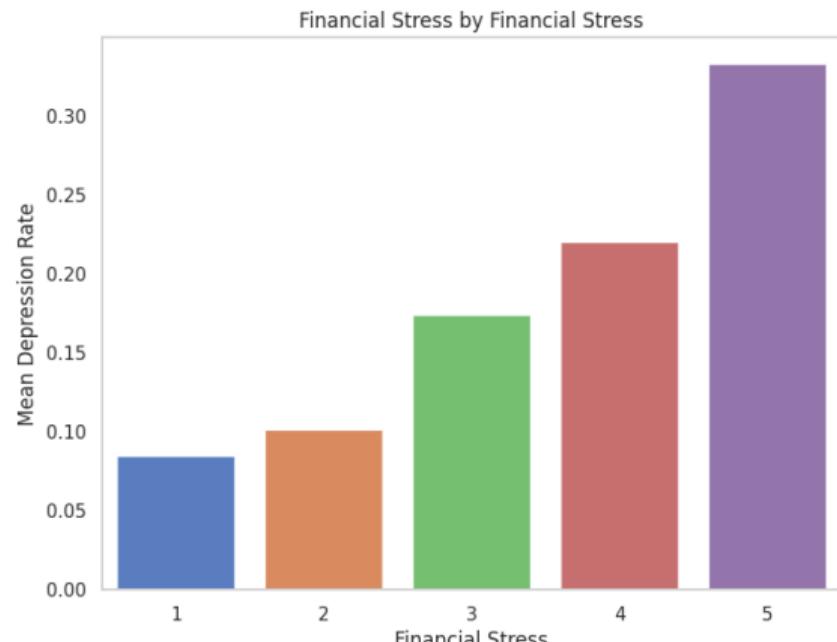
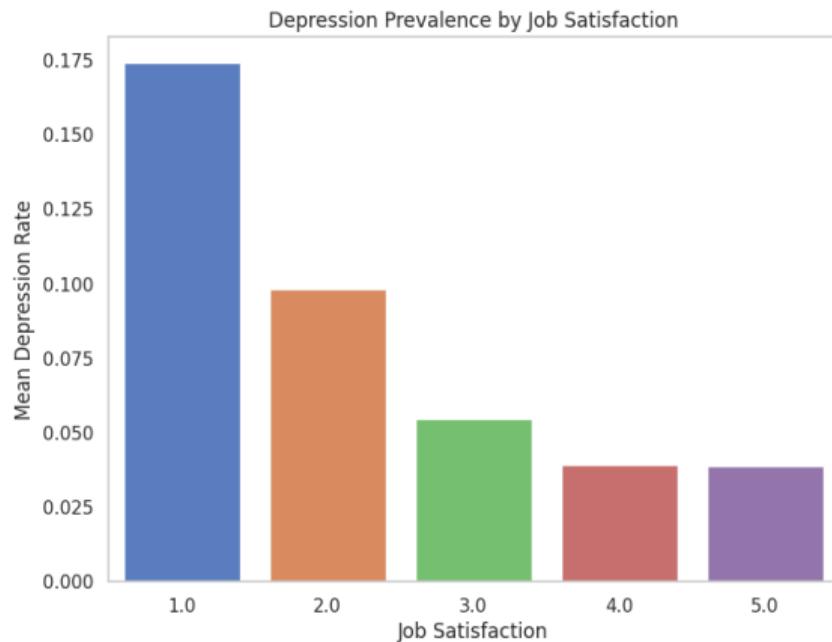
# Exploratory Data Analysis: Features Distribution



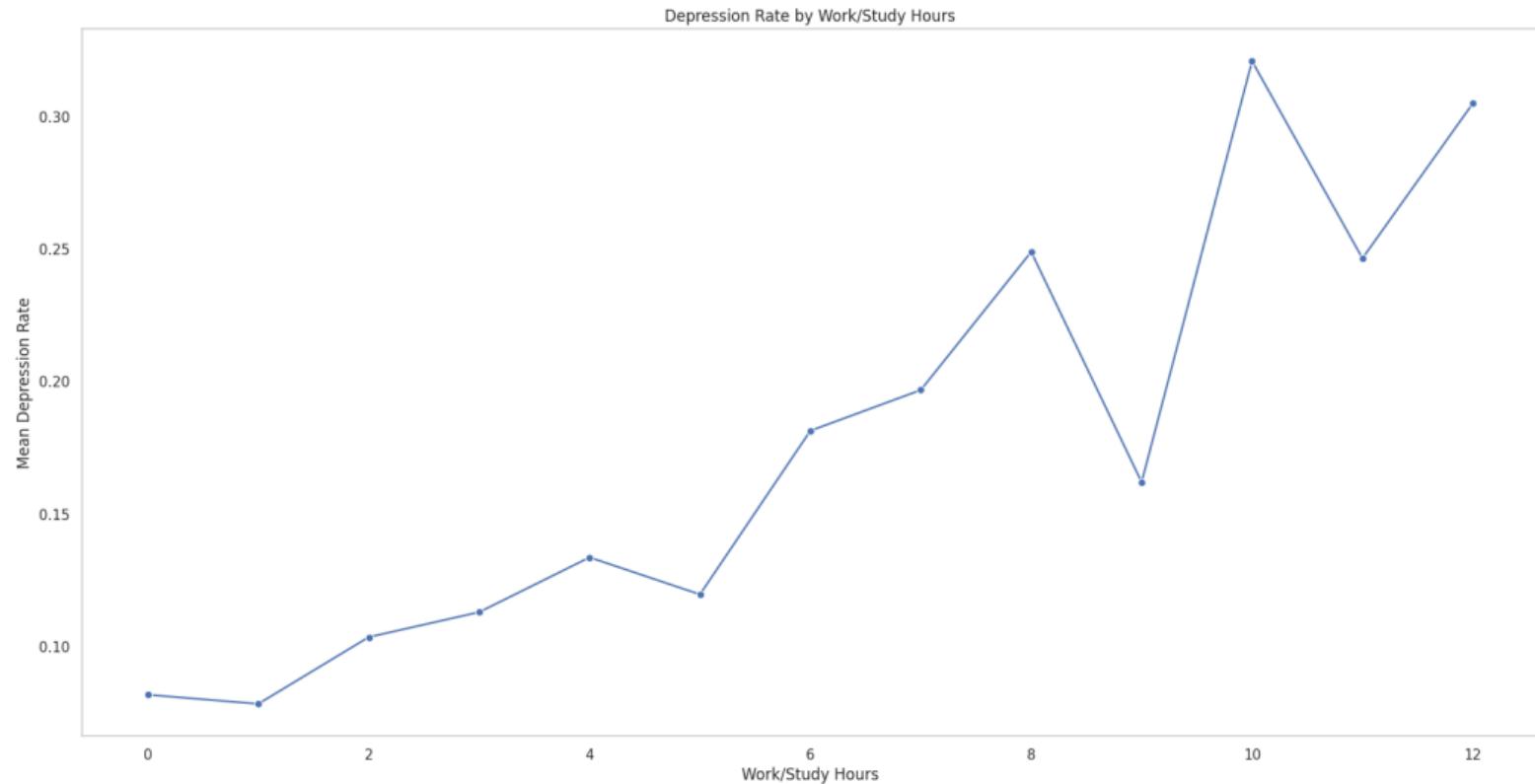
# Exploratory Data Analysis: Features Distribution



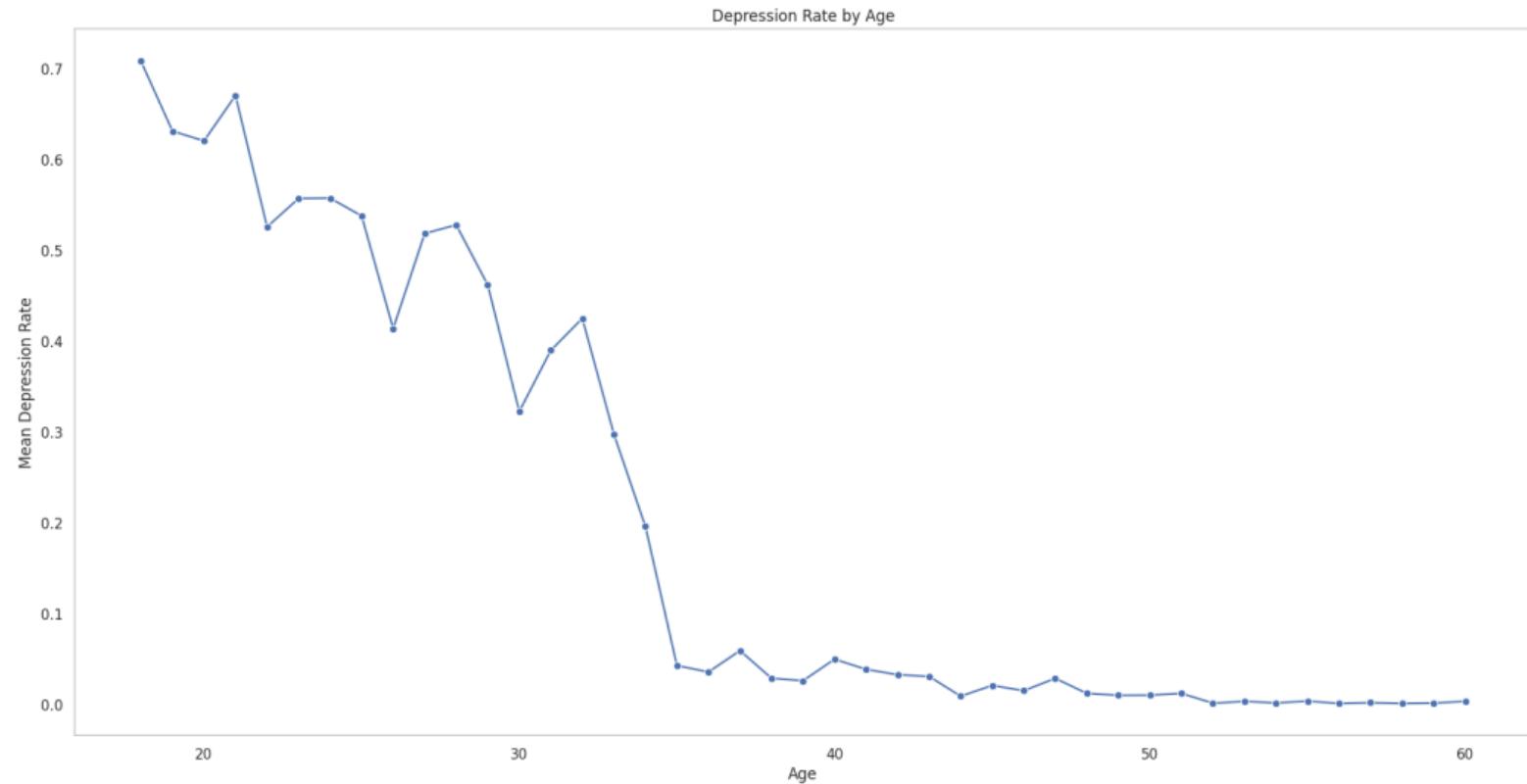
# Exploratory Data Analysis: Features Distribution



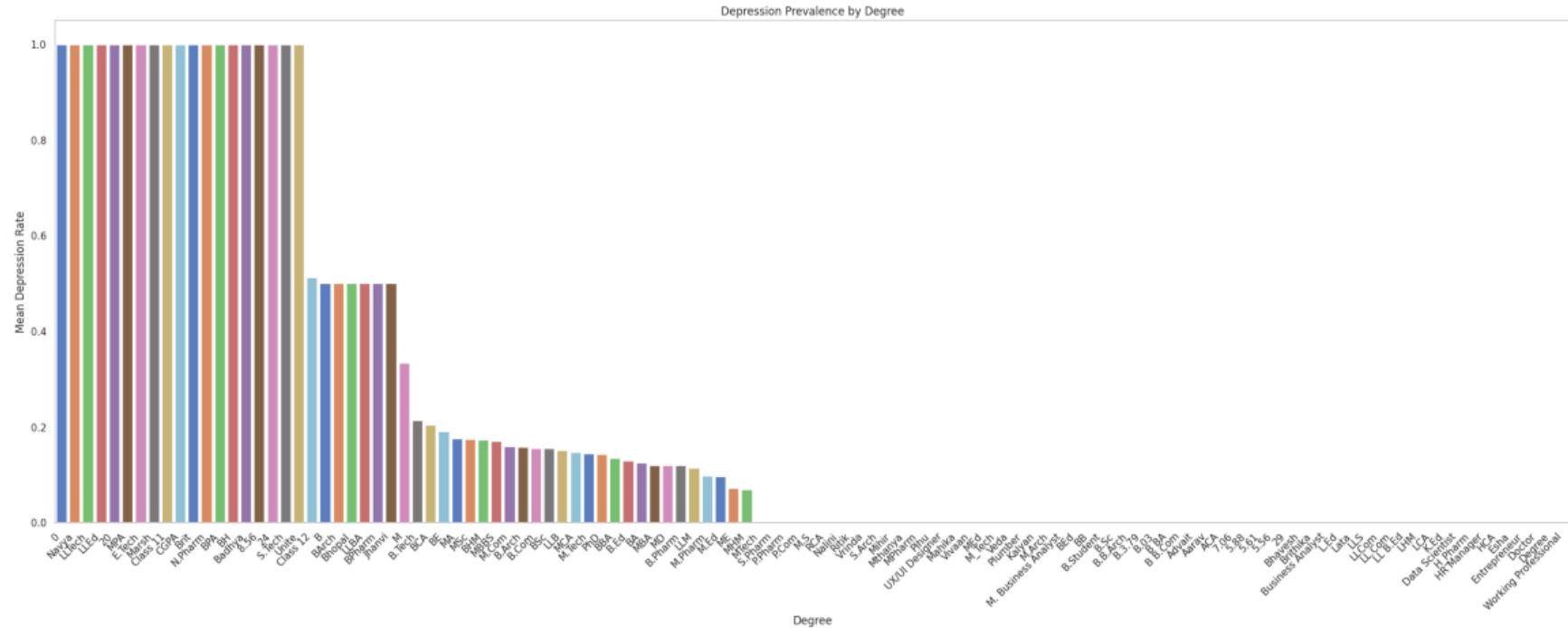
# Exploratory Data Analysis: Features Distribution



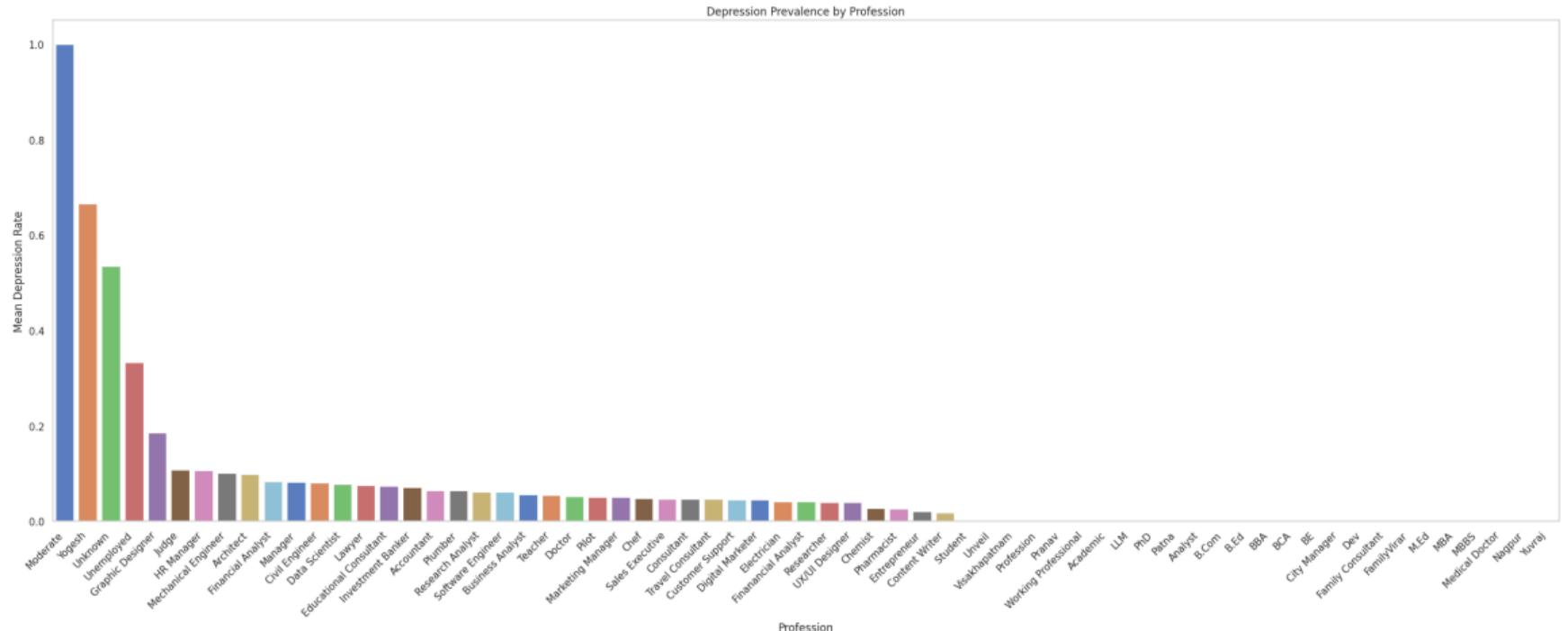
# Exploratory Data Analysis: Features Distribution



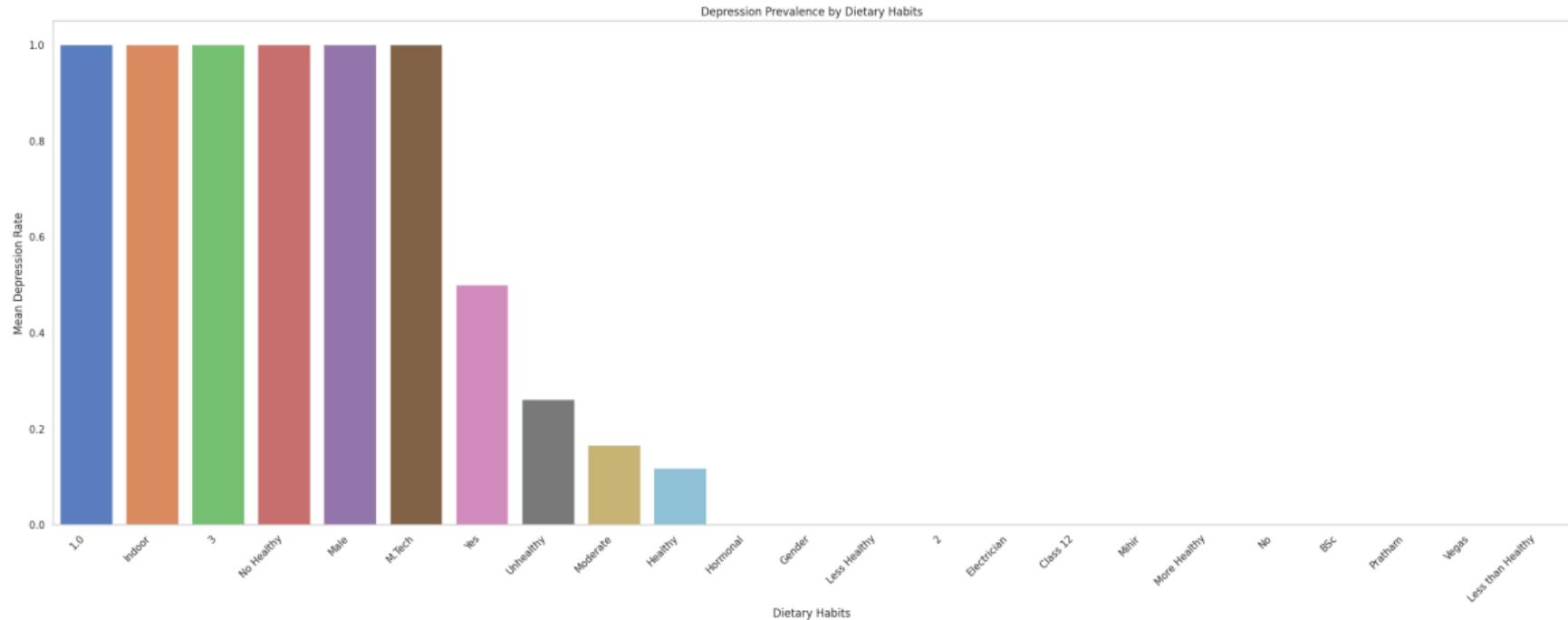
# Exploratory Data Analysis: Features Distribution



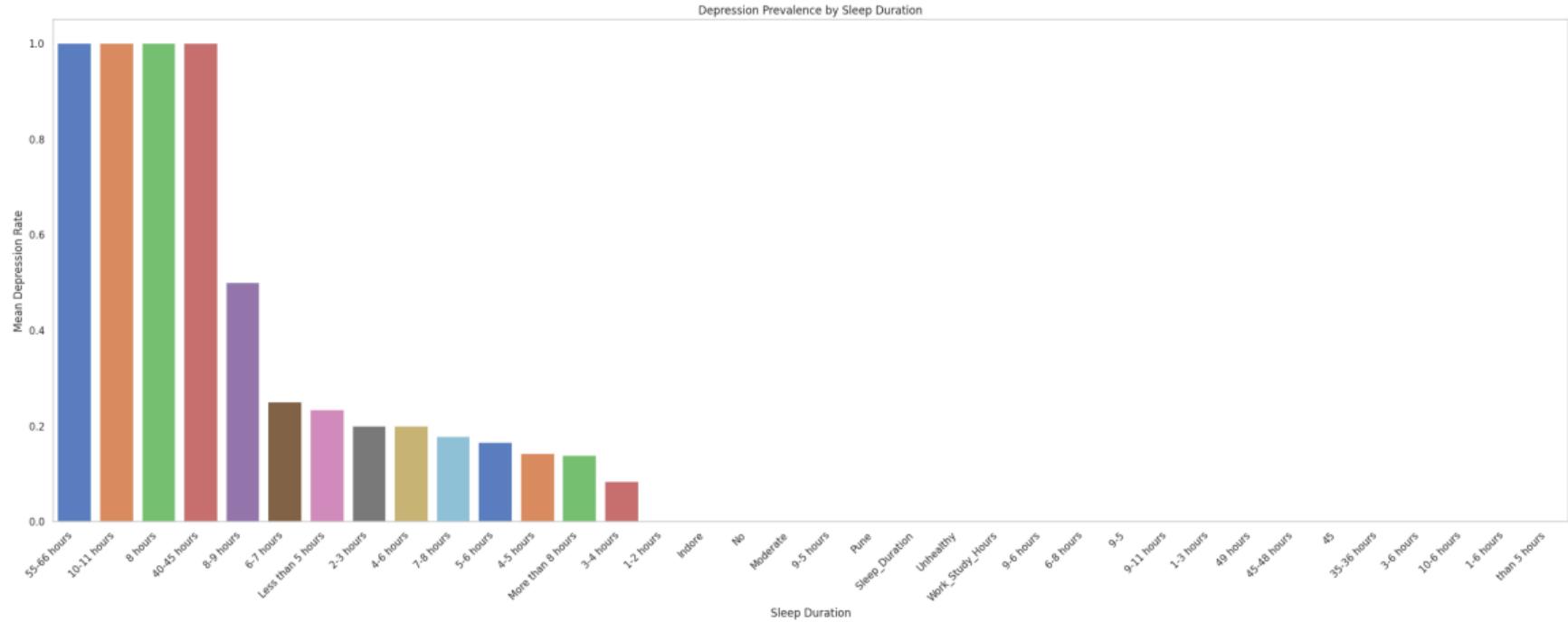
# Exploratory Data Analysis: Features Distribution



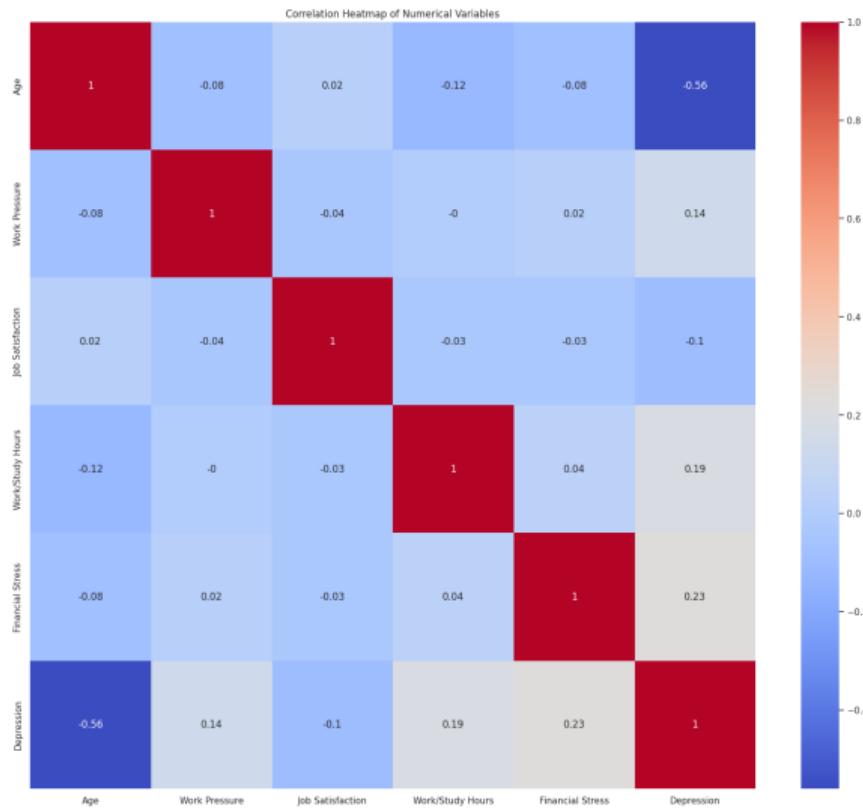
# Exploratory Data Analysis: Features Distribution



# Exploratory Data Analysis: Features Distribution



# Exploratory Data Analysis: Correlation



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# Pre-processing: Missing Values

Process missing values:

- Set threshold of 70 % for null values, remove columns exceeding it
- Filling null values with median for numerical columns
- Filling null values with "Unkown" or mode values for category

# Pre-processing

Apply Label Encoding to each categorical column.

Gender	Age	City	Working Professional or Student	Profession	Work Pressure	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	49	50	1	10	5	2	29	7	33	0	1	2	0	0
1	26	93	1	55	4	3	27	20	63	1	7	3	0	1
1	33	97	0	59	3	3	15	7	21	1	3	1	0	1
1	22	64	1	55	5	1	27	15	28	1	10	1	1	1
0	30	37	1	9	1	1	15	20	28	1	9	4	1	0

Figure: The dataset after transformation

# Modeling

Methods
Decision Tree
Random Forest
LightGBM
Multi-Layer Perceptron

Table: Models name table

*\*Apply Standard Scaler for train data before using Neural Network*

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# Metrics and Evaluation: Confusion matrix

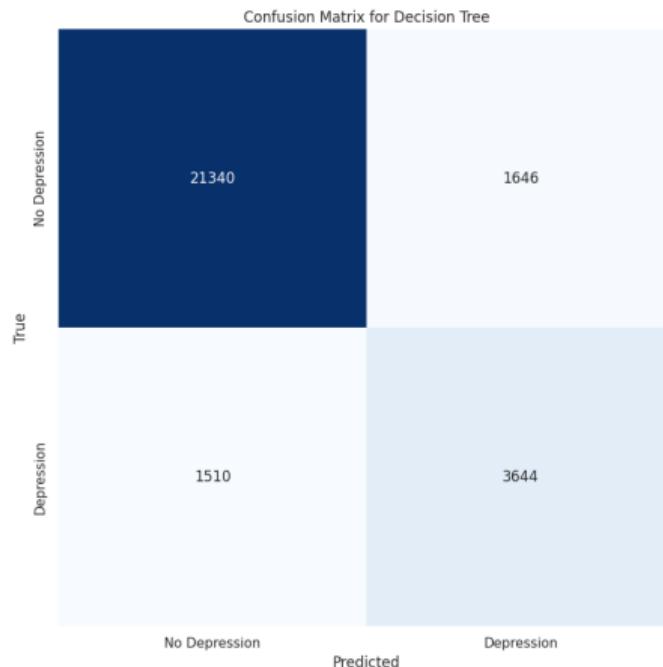


Figure: Confusion Matrix for Decision Tree

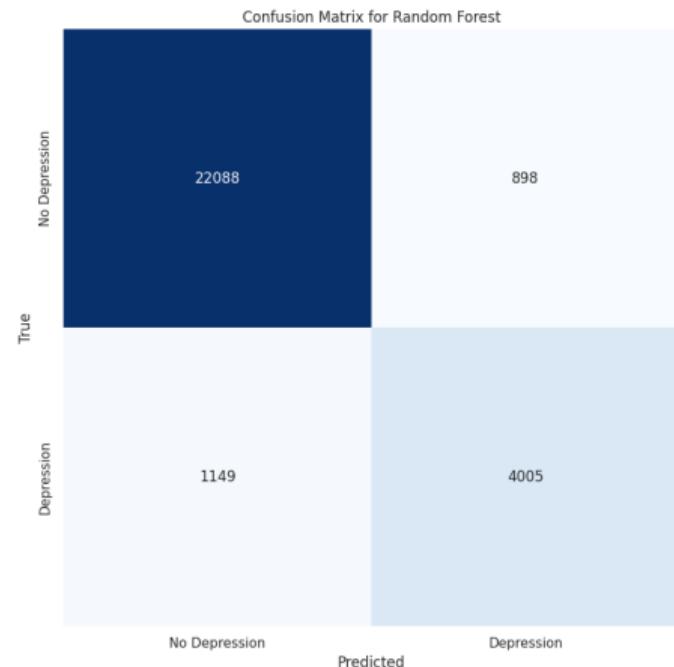


Figure: Confusion Matrix for Random Forest

# Evaluation: Confusion matrix

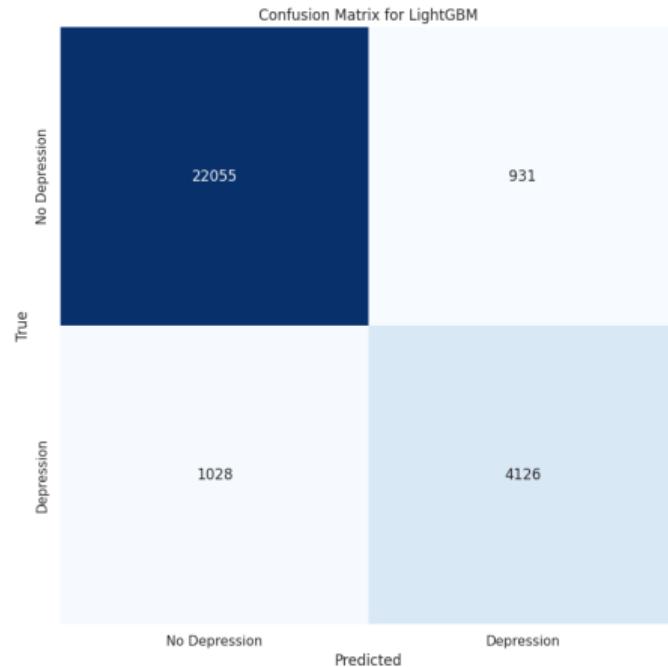


Figure: Confusion Matrix for LightGBM

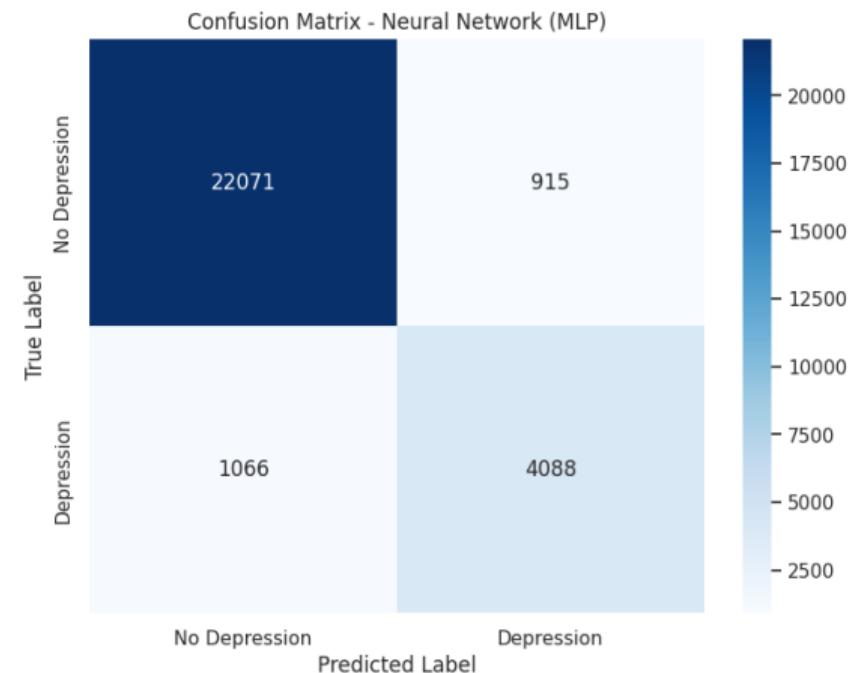


Figure: Confusion Matrix for Multi-Layer Perceptron

# Metrics and Evaluation: ROC curve

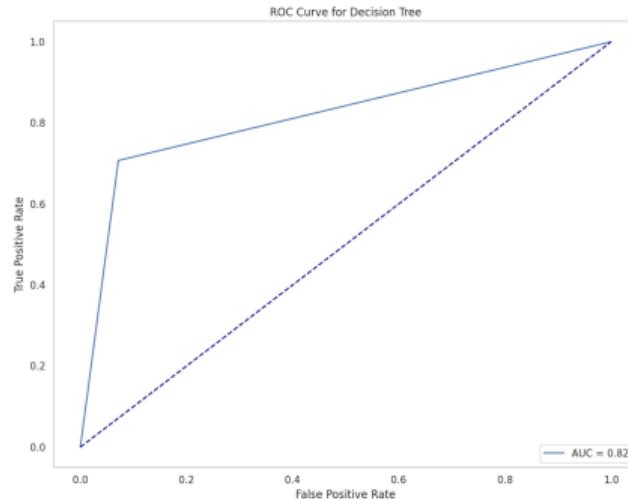


Figure: ROC Curve for Decision Tree

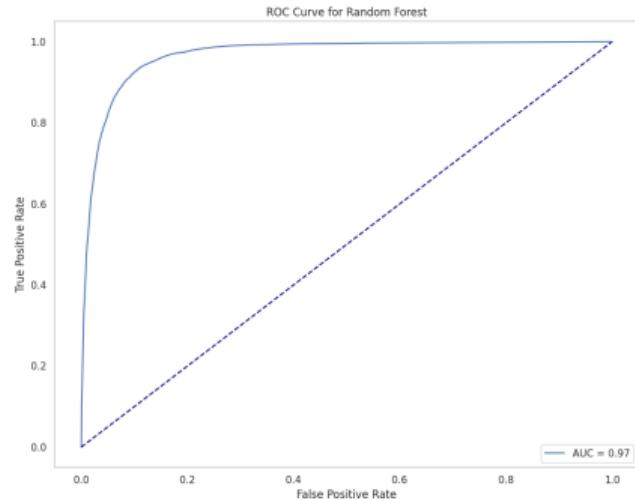


Figure: ROC Curve for Random Forest

# Metrics and Evaluation: ROC curve

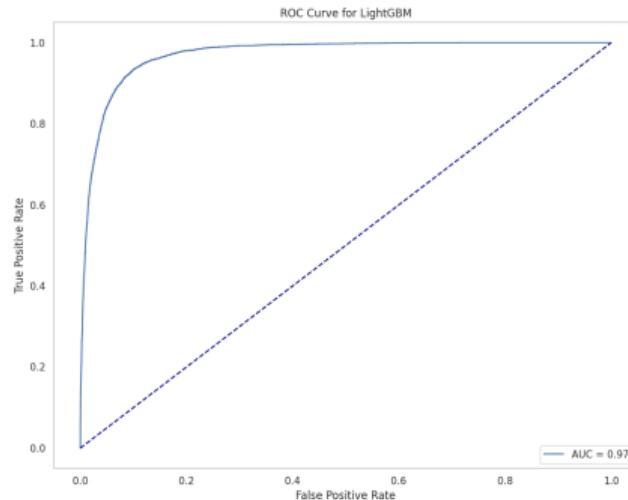


Figure: ROC Curve for LightGBM

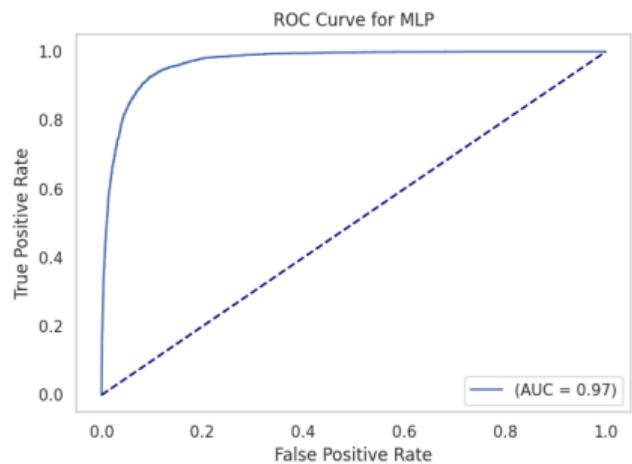


Figure: ROC Curve for MLP

# Metrics and Evaluation: Precision, Recall, F1-score, Accuracy

Methods		Precision	Recall	F1-score	Accuracy
Decision Tree	No Depression	0.93	0.93	0.93	0.89
	Depression	0.69	0.71	0.70	
Random Forest	No Depression	0.95	0.96	0.96	0.93
	Depression	0.82	0.78	0.80	
LightGBM	No Depression	0.96	0.96	0.96	0.93
	Depression	0.82	0.80	0.81	
MLP	No Depression	0.95	0.96	0.96	0.93
	Depression	0.81	0.79	0.80	

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# Conclusion

## Conclusion

- The goal is to use the data to explore factors causing depression and predict the likelihood of experiencing it. Create tools to help organizations diagnose more easily.
- Models such as Random Forest, LightGBM, and Multi-layer Perceptron have demonstrated strong potential in results.

# Future Work

## Conclusion

- **Data Augmentation:** Use data augmentation techniques to enhance the accuracy and generalizability of the predictive model.
- **In-depth Analysis:** Further investigate specific factors that strongly influence depression, such as social, economic, and environmental factors.

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# Demo

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-  Gilles Louppe.  
Understanding random forests: From theory to practice, 2015.
-  Marius-Constantin Popescu, Valentina E Balas, Liliana Perescu-Popescu, and Nikos Mastorakis.  
Multilayer perceptron and neural networks. WSEAS Transactions on Circuits and Systems

# The End

# Tasks Assignment Table

	Van Hung	Ba Huy	Vi Khang	Dang Khoa	Phuc Kien	Duc Lap	Bao Loi
<b>Research and summarize knowledge</b>	x	x	x	x	x	x	x
<b>Design the slides using Latex</b>				x		x	
<b>Implement code demonstration</b>					x		x
<b>Presentation</b>			x			x	
<b>Write the report</b>	x	x					x
<i>Estimate percentage</i>	14%	14%	14%	14%	14%	15%	15%