POSTPARTUM DEPRESSION

Ikram Patel, Sujata Biswas, Alisha James, Andrews Truman, Srikanth Ayyalasomayajula

Table of Contents

Abstract

In the journey of human existence, the significance of health, both physical and mental, is incredibly important. The energy of physical health lays the groundwork for robust living, ensuring individuals can navigate life's challenges with resilience and vigor. However, alongside physical well-being, the complexities of mental health weave an equally crucial thread, shaping individuals' perceptions, emotions, and overall quality of life.

Within this complex framework, Postpartum Depression (PPD) emerges as a touching reminder of the interdependence between physical and mental health, particularly during the vulnerable period following childbirth. As we embark on a journey to explore the depths of PPD through the lens of healthcare analytics, we aim to not only unravel the complexities of maternal mental health but also to forge data-driven pathways towards early detection, intervention, and holistic support for new mothers and their families.

1. Introduction

The journey of motherhood can be a transformative and joyous experience, but for some new mothers, it also brings emotional and psychological challenges. Most new moms encounter postpartum "baby blues" after childbirth, characterized by mood swings, crying spells, anxiety, and difficulty sleeping. However, some mothers face a more severe, long-lasting form of depression known as "postpartum depression" (PPD). Occasionally, this condition can begin during pregnancy, referred to as peripartum depression, and extend into the postpartum period. In rare cases, an extreme mood disorder known as postpartum psychosis may also develop after childbirth.

Postpartum Depression (PPD) is a significant mental health concern that affects mothers worldwide, impacting their well-being and their children's development. Despite its high prevalence and serious consequences, PPD frequently remains undiagnosed and untreated. This oversight can result in prolonged suffering for mothers and potential negative outcomes for their children.

The motivation behind this project arises from the urgent need to close gaps in the detection, understanding, and treatment of PPD. By harnessing the capabilities of healthcare analytics, our objective is to investigate the various biological, psychological, and social factors contributing to PPD. This comprehensive analysis seeks to provide healthcare providers with robust data-driven insights for early detection strategies. By enhancing support for mothers experiencing PPD, we aim to improve both maternal and infant health outcomes, ultimately fostering stronger, healthier families and communities.

2. Related Work

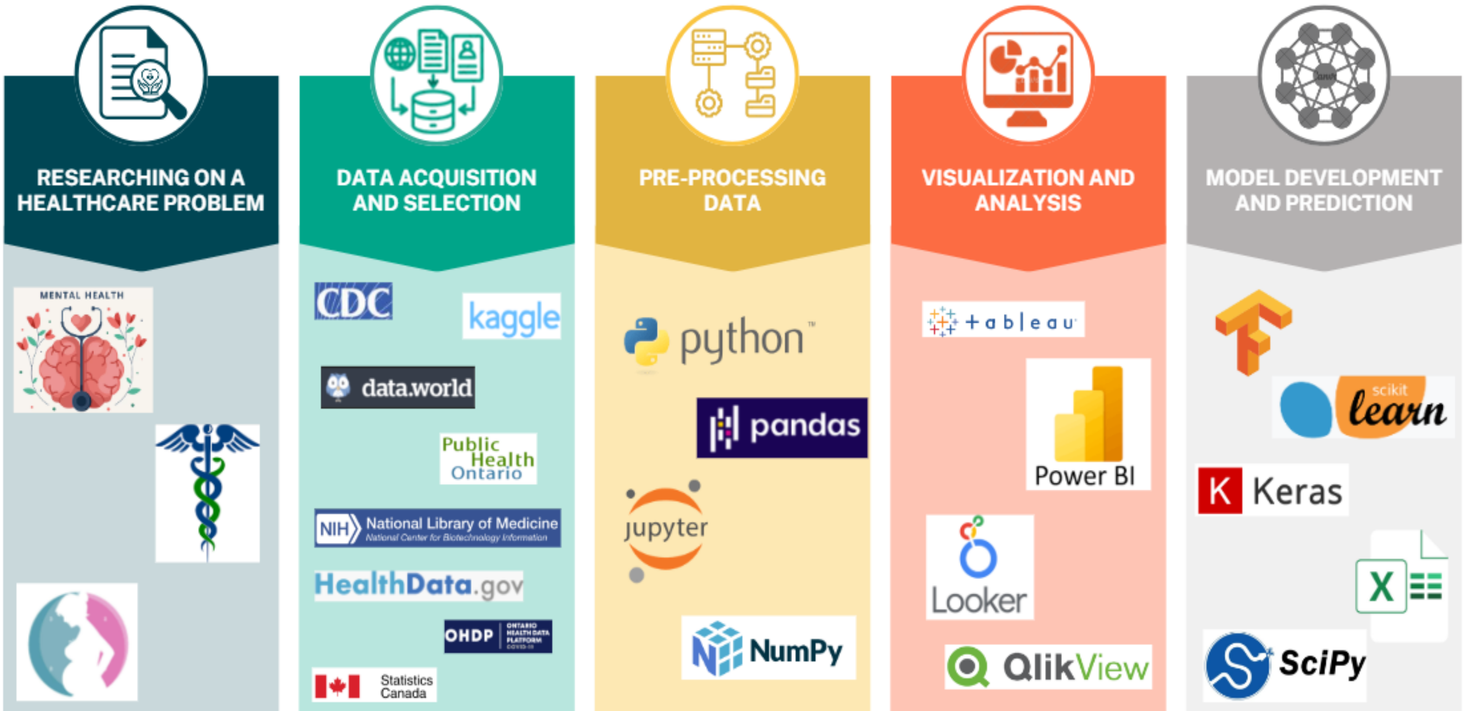
In the field of postpartum depression (PPD), significant research has been conducted to better understand the condition, its causes, symptoms, and treatment options. This section reviews related work and situates the current project in the context of this ongoing research.

Epidemiology and Risk Factors: Several studies have investigated the prevalence of PPD and its associated risk factors. For example, a meta-analysis by Hahn-Holbrook et al. (2018) highlighted the global prevalence of PPD and its correlation with various risk factors such as sleep deprivation, stress, and lack of social support. This paper presents a comprehensive analysis of global trends in postpartum depression (PPD) prevalence and examines the impact of economic and health factors on PPD rates. The researchers conducted a systematic review, meta-analysis, and meta-regression analysis of 291 studies from 56 countries. Their findings highlight the relationship between national economic health, access to healthcare, and the prevalence of PPD. This research provides valuable insights into how societal-level factors influence PPD rates across different countries, offering a broader context for understanding the current project.

Machine Learning in Mental Health: Recent work has explored the use of machine learning in mental health diagnosis and prediction, including PPD. For instance, a study by Santos et al. (2020) utilized machine learning algorithms to predict PPD based on social media data, demonstrating the potential of data-driven approaches in this field. This research explores the application of machine learning techniques in predicting postpartum depression. The authors used a variety of machine learning algorithms to analyze data from pregnant and postpartum women and identify potential risk factors for PPD. The study demonstrates how machine learning can be leveraged to enhance the early detection of PPD and guide targeted interventions. This work is closely related to the current project's focus on using data-driven approaches to understand and address postpartum depression, emphasizing the potential of advanced analytics in improving maternal mental health outcomes.

Predictive Modeling for Suicide Risk: In parallel with PPD research, predictive modeling for suicide risk assessment has been a growing area of study. Works such as those by Franklin et al. (2017) have used machine learning algorithms to identify individuals at high risk of suicide based on various risk factors. This research is important because it demonstrates the potential of predictive modeling to help healthcare professionals intervene early and provide support to individuals at high risk. These models can offer valuable insights into the complex interplay of risk factors, which may include mental health issues, family history, socioeconomic status, and other variables.

3. Project Flow/Architecture



Above diagram describes the flow of the project from Identifying a problem till building a Machine learning model to predict the results. Below are steps involved in the flow of the project.

3.1. Researching and Identifying a Healthcare problem:

The project began by identifying a pressing health care issue, which led to the selection of Postpartum Depression (PPD) as the focus area. Recognizing the significant impact of PPD on maternal mental health, the objective was to address the challenges associated with early detection and intervention for this condition. This step involved extensive research and literature review to understand the complexities and implications of PPD.

3.2.Data Acquisition and Selection:

Following the identification of PPD as the target problem, the next step involved acquiring relevant data sets for analysis. Various sources were explored to gather comprehensive data on PPD symptoms, patient demographics, and other related factors. The selection process emphasized the quality and relevance of the data, ensuring that it aligned with the project's objectives and could support effective analysis and modeling.

3.3.Pre-processing Data:

Once the data sets were acquired, they underwent thorough pre-processing to ensure consistency, accuracy, and readiness for analysis. This step involved cleaning the data to remove errors, inconsistencies, or missing values, as well as transforming categorical variables into numerical formats suitable for machine learning algorithms. Statistical technique such as bootstrapping was also applied to enhance the number of records in the data set to make it suitable for Machine learning.

3.4.Visualization and Analysis:

With the pre-processed data in hand, the project proceeded to visualize and analyze key patterns, trends, and relationships within the dataset. Visualization techniques such as charts, graphs, and heatmaps were employed to gain insights into the distribution of variables and identify potential correlations or dependencies. Exploratory data analysis (EDA) techniques were used to uncover underlying patterns and inform subsequent modeling decisions.

3.5. Model Development and Prediction:

The final step of the project involved developing predictive models to identify and classify individuals at risk of PPD. Machine learning algorithms, particularly classification models like Random Forest, were trained on the pre-processed data to predict the likelihood of PPD based on input features. Model evaluation and validation techniques were employed to assess the performance and accuracy of the models, ensuring their reliability and effectiveness in real-world scenarios.

4. Data Acquisition

The dataset utilized in this project is originally collected from a medical hospital using questionnaire administered through survey and is currently uploaded on kaggle.com by researcher. The dataset initially consisted of 1503 records. To enhance its size, bootstrapping technique was used, resulting in an expansion to one and half million records. It includes 10 attributes.

Attribute	**Description**
Age	The age of the respondents, typically categorized into age groups (e.g., 25-30, 30-35, etc.).
Feeling sad or Tearful	Respondents' emotional state, including sadness or tearfulness.
Irritable towards baby & partner	The degree of irritability or annoyance respondents feel towards their baby and partner.
Trouble sleeping at night	The presence of sleep disturbances, such as difficulty falling or staying asleep.
Problems concentrating or making decisions	Respondents' ability to focus and make decisions, which may be impaired.
Overeating or loss of appetite	Changes in eating habits, including either overeating or a decrease in appetite.
Feeling anxious	The presence of anxiety or nervousness in respondents.
Feeling of guilt	Respondents' sense of guilt, often related to perceived failures or inadequacies.
Problems of bonding with baby	The extent to which respondents struggle to establish a connection with their baby.
Suicide attempt	Instances where respondents have attempted suicide, indicating a serious mental health issue.

5. Data Preprocessing and Cleaning

We started by loading the provided dataset into a Pandas DataFrame, which facilitated the initial examination of the dataset. The original dataset contained 1,503 records. To increase its size and improve model robustness, we applied the bootstrapping technique, expanding the dataset to approximately 1.5 million records. This expansion enabled more reliable statistical analysis and machine learning modeling.

After performing bootstrapping technique to increase the size of the data set for Machine learning, we compared the statistics of the original data with the newly created data set to cross validate the accuracy of the enhanced data.

Upon loading the dataset, we generated a comprehensive report outlining the data types of each column. Specifically, there were 10 categorical columns, representing different aspects of postpartum depression (PPD) and related symptoms.

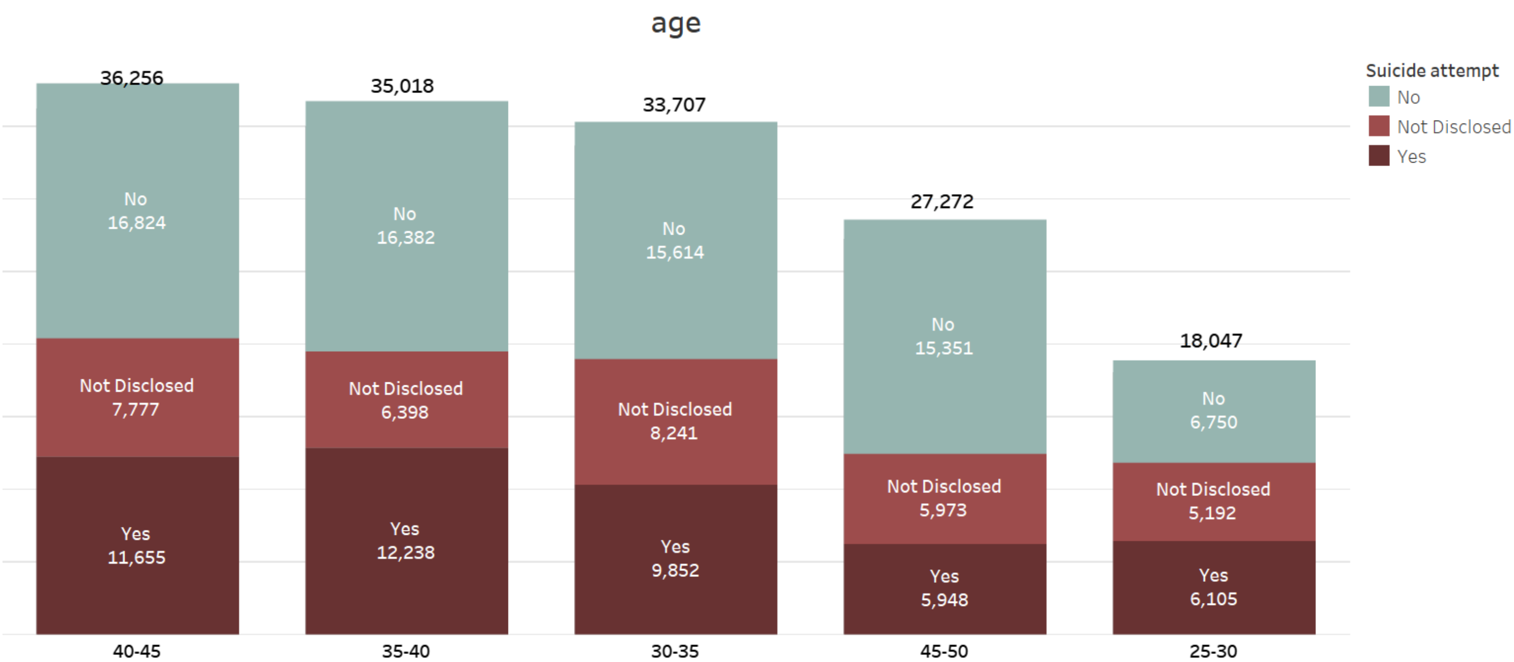
Next, we calculated a statistical summary of the data, which provided insights into the dataset's central tendencies and dispersions. This summary included measures such as count, unique, top, and frequency for categorical columns, giving us a better understanding of the data distribution and the most common responses.

Additionally, we assessed the dataset for the presence of missing values. Three columns with missing data were identified, which could potentially introduce bias or inaccuracies in subsequent analyses. To maintain data integrity and ensure the validity of our findings, we applied appropriate handling methods such as imputation or removal of missing values.

By thoroughly examining the dataset and addressing any issues, we established a solid foundation for the subsequent stages of data analysis and machine learning modeling. This approach ensured that our findings and models were based on a robust and clean dataset, allowing for more accurate insights and predictions.

6. Data Visualisation

We did analysis by performing data visualization using Tableau. This approach allowed us to create intuitive and insightful visual representations of the data, helping us to better understand the relationships and trends within the dataset. The data provide significant insights into the complex relationship between postpartum challenges and suicidal attempts in mothers. The analysis of various factors and survey responses presents a comprehensive view of the multifaceted nature of postpartum depression (PPD) and its impact on maternal mental health:



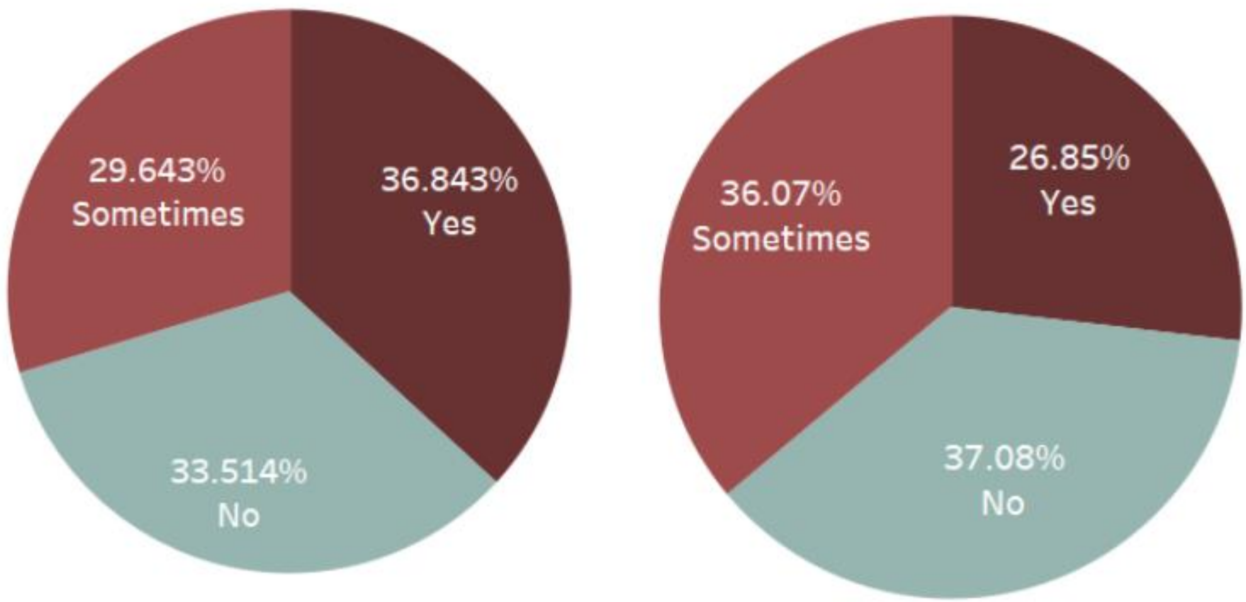
The chart illustrates the distribution of suicide attempts among patients categorized by age brackets. From the visual depiction, it's evident that the highest frequency of suicide attempts occurs within the age bracket of 40-45, while the lowest is observed in the 25-30 age group.

Additionally, the age group 35-40 exhibits the highest number of suicide attempts, contrasting with the lowest count found in the 45-50 age bracket.

Conversely, the age group 30-35 demonstrates the highest frequency of patients who did not attempt suicide, with the lowest count noted in the 25-30 age bracket.

Overall, it highlights varying trends, with the 40-45 age group exhibiting the highest frequency and the 25-30 age group the lowest. These insights emphasize the need for tailored interventions to address age-specific vulnerabilities and support mental health across diverse demographics.

Irritable towards Baby & Partner vs Problems Bonding with Baby

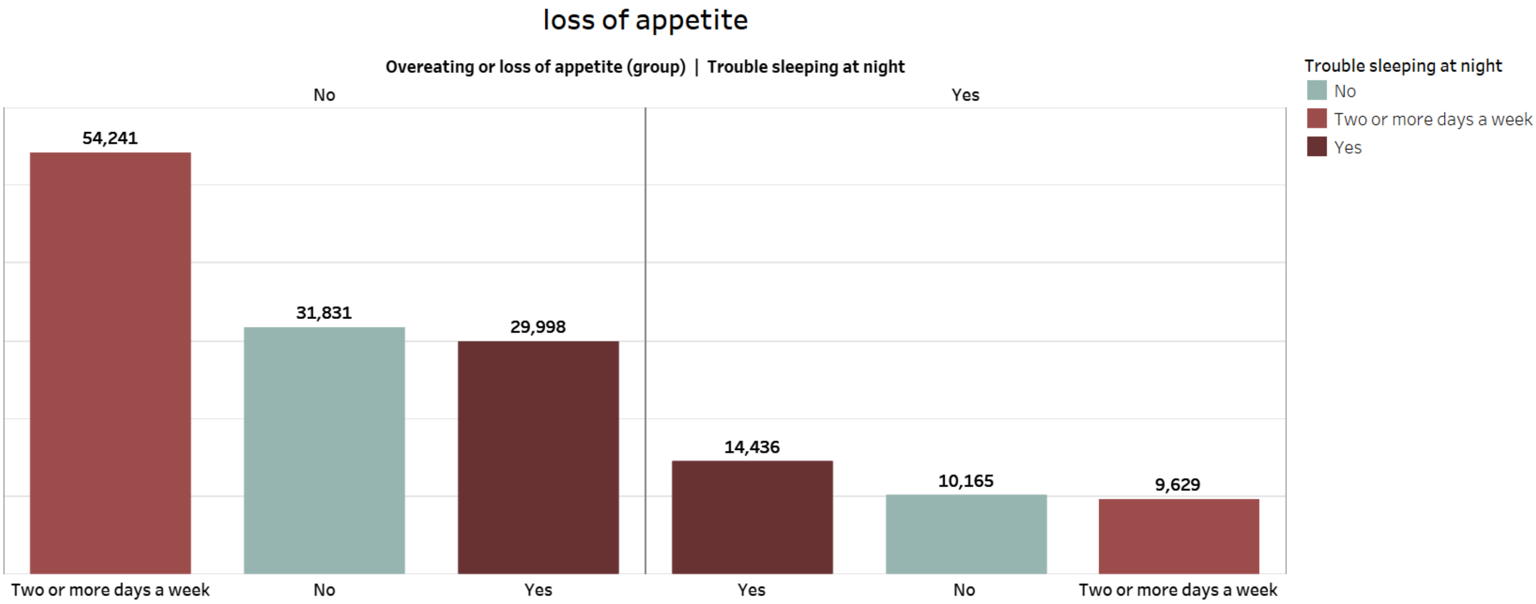


Above comparison pie charts show the comparison between patient irritable towards baby or partner vs patients facing problems bonding with their baby.

The comparison illustrates that approximately 66% of patients are irritable towards their baby and partner, whereas 34% are not.

Whereas approximately 63% of patients are facing problems bonding with baby and 37% are not.

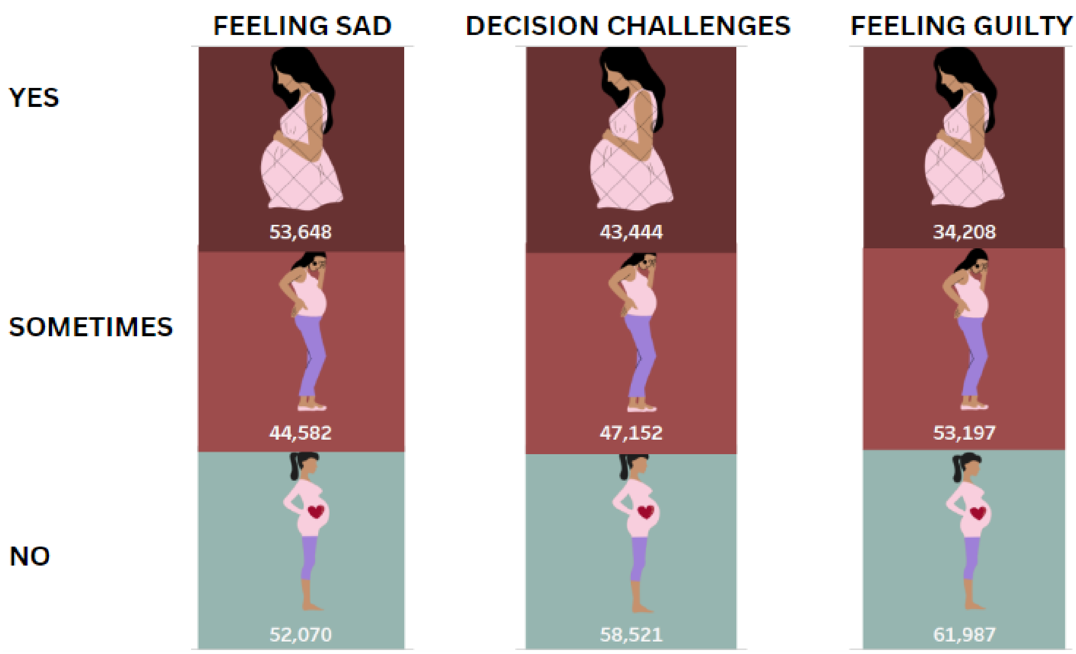
Overall, it highlights that majority of the patients usually face problems bonding with baby and they also feel irritated during the Post partum period.



The bar chart displays the prevalence of overeating or loss of appetite issues against patients experiencing trouble sleeping at night.

Notably, the data indicates a stark contrast, with approximately 54,000 records depicting overeating or loss of appetite problems occurring more than two days a week.

Whereas around 14,000 records detail issues related to sleep disturbances at night.



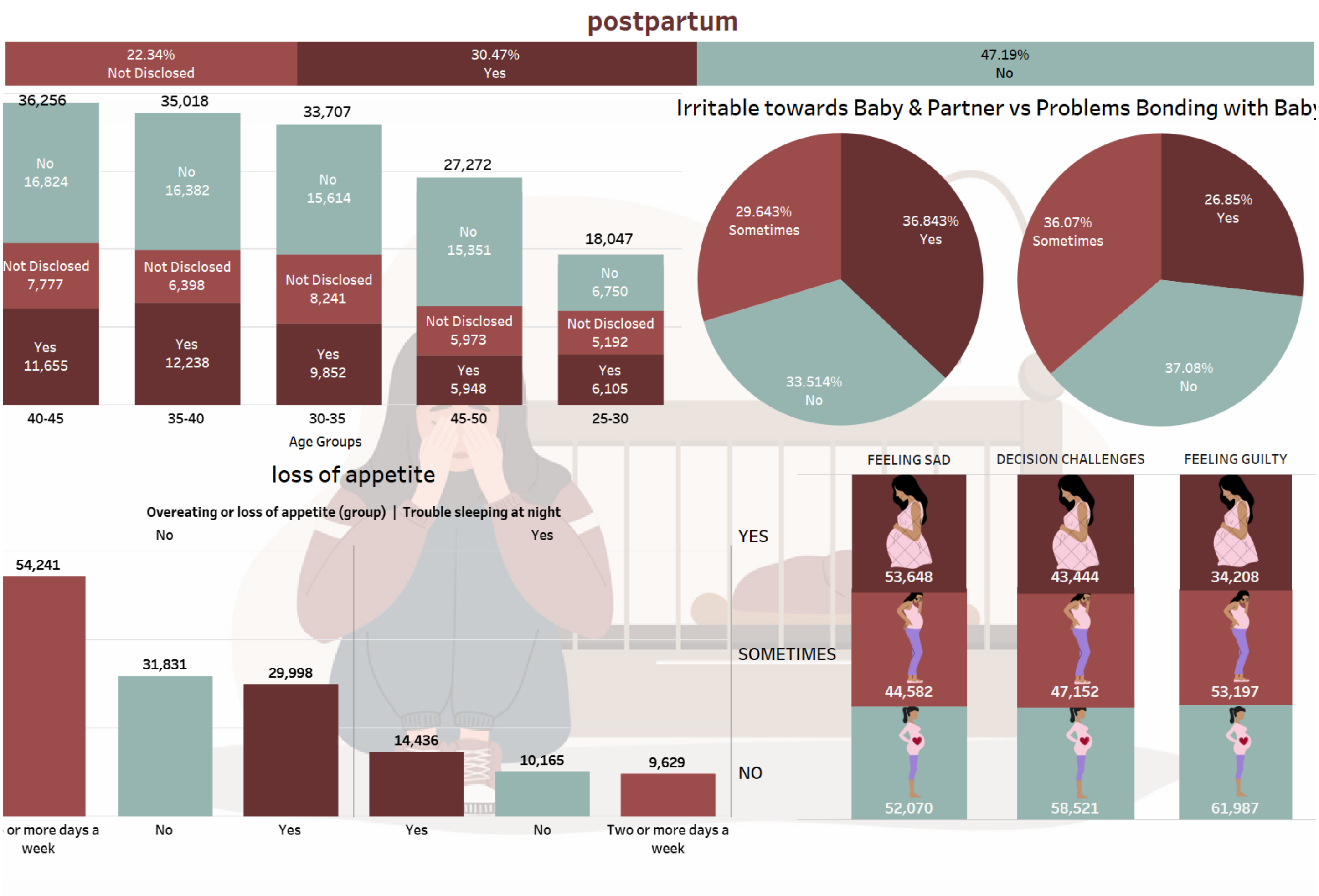
The above stacked bar chart comparisons give us a brief understanding of how frequently the patient felt sad, had problems making decisions or felt guilty.

The chart clearly shows that more than 50k records state that they did feel sad, more than 40k records stating that the patients did face problems making decisions while around 35k records stated that they did feel guilty.

These factors have seen to be some of the most crucial emotions to have been felt eventually leading to a much adverse step for the patients.

The chart signifies that a huge number of patients have experienced these symptoms and is a major problem causing inconvenience to the patients.

ST. CLAIR COLLEGE



- About 22.34% of respondents across all age groups did not disclose information regarding suicide attempts. This could indicate a persistent stigma surrounding mental health issues, discouraging open discussion and potentially leading to underreporting. This lack of disclosure can hinder timely and effective intervention for mothers in distress.

- The data reveals a decrease in suicide attempts as age increases, with younger age groups (25-30, 30-35) being more vulnerable. Younger mothers may face unique stressors such as adapting to new roles and life changes, making them more susceptible to emotional challenges and suicide risk.

- Various factors such as trouble bonding with the baby, loss of appetite, irritability towards the baby and partner, and feelings of sadness have emerged as contributing factors to PPD which if not handled early can lead to suicidal attempts. This complexity highlights the need for comprehensive assessment and support for mothers experiencing PPD.

- A significant portion of respondents (56.42%) reported feeling irritable towards the baby and partner, possibly due to stress, sleep deprivation, or temperament changes associated with PPD. Even occasional irritability (20.52%) may reflect underlying emotional challenges that require attention.

- Nearly one-third (30.59%) of respondents reported difficulty bonding with their baby, with another 23.82% experiencing this challenge sometimes. Difficulty bonding can affect a mother's sense of fulfillment and emotional connection with her child, potentially exacerbating PPD symptoms.

- The high number of respondents feeling sad consistently (13,857) or occasionally (6,525) underscores the emotional burden PPD can place on mothers. Sadness can be debilitating and impact daily life and overall well-being.

- The significant proportion of respondents facing decision-making difficulties (20,566 "Yes" and 5,765 "Sometimes") suggests that cognitive challenges are a common aspect of PPD. These challenges can affect a mother's ability to make decisions for herself and her baby, potentially contributing to feelings of inadequacy and deepening emotional distress.

- A substantial number of respondents (12,320) reported experiencing feelings of guilt, a common symptom of PPD. This could stem from perceived failures in motherhood or difficulty adjusting to new responsibilities, perpetuating a cycle of self-doubt and emotional burden.

- Overall, the findings emphasize the need for comprehensive screening and support for mothers experiencing PPD-related symptoms. Early identification and intervention can help improve outcomes for both the mother and child, highlighting the critical role of healthcare providers in providing tailored care and resources.

7. Prediction Using Machine Learning Model

The predictive modeling process sought to forecast whether a patient has suicidal thoughts by employing machine learning algorithms. Initially, an appropriate model was selected based on the nature of the dataset and the specific problem at hand. We chose a Random Forest Classifier due to its robustness, flexibility, and ability to handle diverse data types. This algorithm is particularly effective for classification tasks and can efficiently manage large datasets with numerous features.

The selected model underwent extensive training on the available data, which allowed it to identify intricate patterns and relationships within the dataset. This training phase is crucial as it enables the model to learn and understand the nuances of the data, ultimately refining its predictive capabilities. To evaluate the model's performance, we tested it on a separate validation set, which mirrors real-world data while remaining distinct from the training set.

During the evaluation, accuracy score was employed as the primary metric, as it measures the proportion of correct predictions made by the model. The Random Forest Classifier demonstrated exceptional performance, achieving a remarkable accuracy score of 0.996. This high level of accuracy indicates the model's ability to provide reliable predictions and its potential to serve as a powerful tool in assessing a patient's risk of suicidal thoughts.

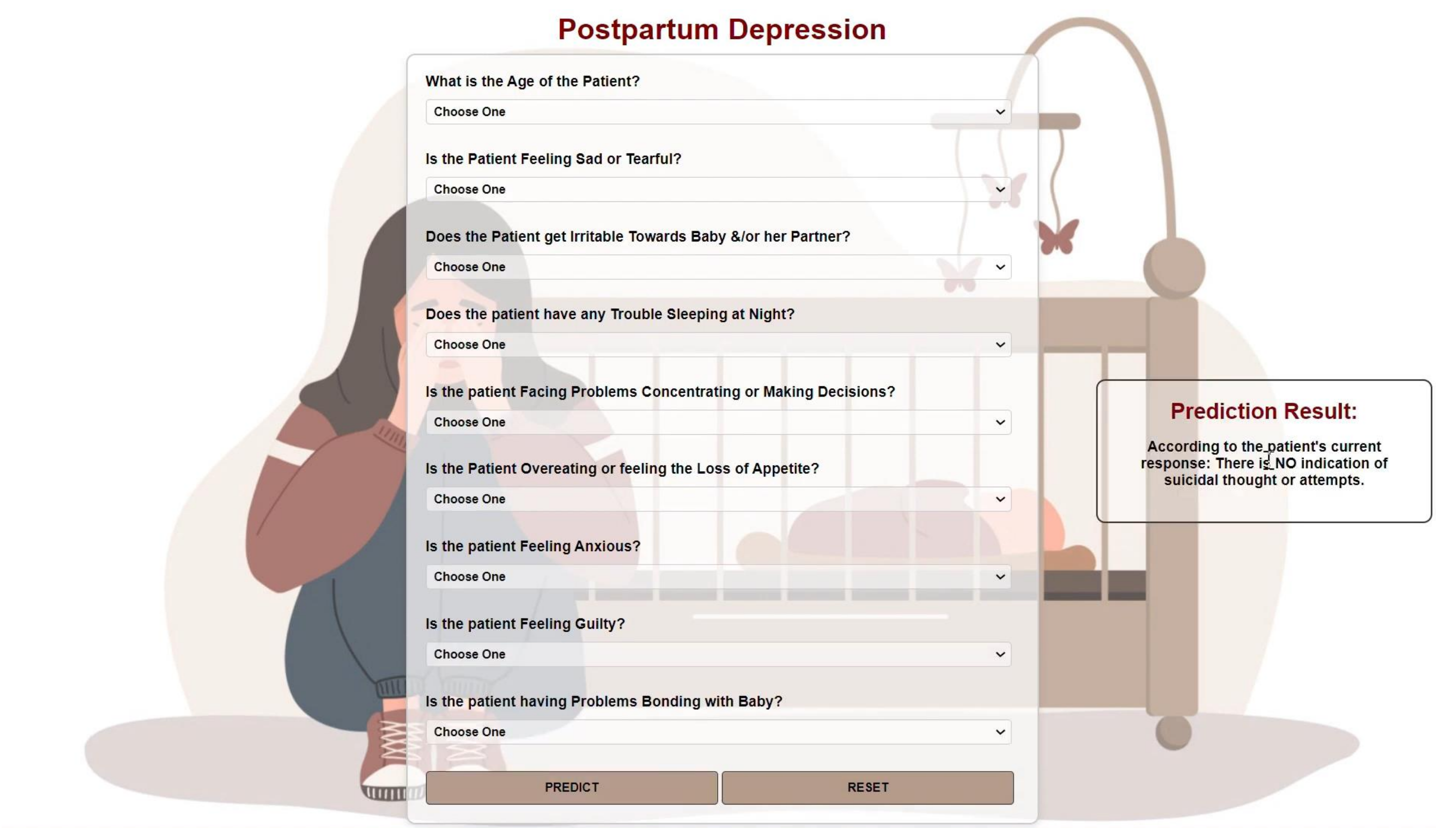
Following the successful validation, the model was deployed for making predictions on new, unseen data. This real-time deployment will be helpful for providing immediate assessments and predictions regarding a patient's potential suicidal thoughts. By facilitating timely and effective interventions, this approach can greatly improve the care and support provided to individuals at risk, ultimately contributing to better mental health outcomes.

After deploying the model, a user interface (UI) was created for prediction. The UI was integrated with the model using Python Flask, allowing for seamless interaction and user-friendly predictions. This integration ensures that healthcare providers and other users can easily access the model's predictions, enabling them to make informed decisions and interventions more efficiently.

8. Final Product: Web Interface

The above Web Interface gives the list of questions that the healthcare professional would want to ask to any of his/her patients post childbirth to record their responses to help understand if the patient is likely to have any suicidal thoughts or would take any steps in committing one.

Based on these prediction results the healthcare professional can help them further through early detection and any precautionary measures that they could take to help prevent such an unfortunate event from happening.



Above shows the prediction result for the responses recorded by doctor as shown in the previous snapshot.

The predictions are received in three categories based on the responses of the patient being:

1. NO: "There is NO indication of suicidal thought or attempts."
2. PREFER NOT TO SAY: "The patient is LIKELY to have suicidal thoughts or has plans of committing one."
3. YES: "The patient is EXTREMELY LIKELY to have suicidal thoughts or has plans of committing one."

9. Conclusion

The analysis conducted using data visualization tools like Tableau provided crucial insights into the complex relationships between postpartum challenges and the risk of suicidal attempts in mothers. The findings highlight the multifaceted nature of postpartum depression (PPD) and its profound impact on maternal mental health.

Key conclusions from the analysis include:

Stigma and Underreporting: A significant portion of respondents did not disclose information about suicide attempts, pointing to the persistent stigma around mental health issues. This can lead to underreporting and hinder timely intervention and support for mothers in distress.

Age-Related Vulnerability: Younger age groups, particularly those aged 25-30 and 30-35, are more vulnerable to suicidal attempts due to unique stressors such as adjusting to new roles and life changes.

Complex Factors Contributing to PPD: Various factors like trouble bonding with the baby, loss of appetite, irritability towards the baby and partner, and feelings of sadness emerged as potential contributors to PPD and suicidal attempts. Addressing these issues early is crucial for preventing further complications.

Emotional and Cognitive Challenges: The high prevalence of irritability, sadness, decision-making difficulties, and feelings of guilt among respondents underscores the emotional and cognitive toll PPD can have on mothers. These challenges can impact daily functioning and overall well-being, necessitating comprehensive support.

Importance of Early Intervention: The findings emphasize the need for early identification and intervention for mothers experiencing PPD-related symptoms. Comprehensive screening and support can improve outcomes for both the mother and child, highlighting the critical role of healthcare providers in offering specialized care and resources.

In addition to data analysis, the use of machine learning models, such as the Random Forest Classifier, has demonstrated the potential to predict suicidal thoughts in patients with high accuracy. This predictive approach can facilitate timely interventions and support for at-risk individuals, ultimately contributing to better mental health outcomes.

Overall, these findings underscore the importance of adopting a comprehensive approach to postpartum mental health challenges. By combining data-driven insights with individualized care and targeted interventions, healthcare providers can more effectively identify and address the unique needs of each mother. This holistic strategy not only improves outcomes for mothers by providing timely and relevant support but also fosters better long-term well-being for both the mother and child. Moreover, promoting awareness and education about postpartum mental health can help reduce stigma and encourage open conversations, ultimately leading to earlier interventions and improved mental health care for all mothers.

Contributions

Team Member	Contribution
Ikram Patel	Research on Project Ideas Searching dataset related to the topic. Project Proposal preparation Data Preprocessing and cleaning Data Visualization and creating Dashboard using Tableau. Prediction using machine learning. User interface creation Project Report Preparation
Sujata Biswas	Research on Project Ideas Searching dataset related to the topic. Project Proposal preparation Data Preprocessing and cleaning Data Visualization and creating Dashboard using Tableau. Prediction using machine learning. User interface creation Project Report Preparation
Alisha James	Research on Project Ideas Searching dataset related to the topic. Project Proposal preparation Exploratory Data Analysis Prediction using machine learning. Project Report Preparation
Andrews Truman	Research on Project Ideas Searching dataset related to the topic. Project Proposal preparation Exploratory Data Analysis Prediction using machine learning. Project Report Preparation
Srikanth Ayyalasomayajula	Research on Project Ideas Searching dataset related to the topic. Project Proposal preparation Exploratory Data Analysis Prediction using machine learning. Project Report Preparation

References

- Mpwolke. (2023, January 27). *Postpartum depression*. Kaggle. https://www.kaggle.com/code/mpwolke/postpartum-depression/notebook

- Author links open overlay panelMário W.L. Moreira a b, a, b, c, d, f, e, g, Highlights•Postpartum depression (PPD) prediction using real pregnancy database. As emotion-aware smart systems evolve, Biaggi, A., Glover, V., Brummelte, S., Putnam, K. T., Gravina, R., Yan, Z., Zhang, Q., Jin, C., Rutkowski, L., … Demirel, G. (2018, July 9). *Postpartum depression prediction through pregnancy data analysis for emotion-aware Smart Systems*. Information Fusion. https://www.sciencedirect.com/science/article/abs/pii/S1566253518301295

- (PDF) economic and health predictors of national postpartum depression prevalence: A systematic review, meta-analysis, and meta-regression of 291 studies from 56 countries. (n.d.). https://www.researchgate.net/publication/322867984_Economic_and_Health_Predictors_of_National_Postpartum_Depression_Prevalence_A_Systematic_Review_Meta-analysis_and_Meta-Regression_of_291_Studies_from_56_Countries

- Fischbein, R., Cook, H. L., Baughman, K., & Díaz, S. R. (2022, November 21). *Using machine learning to predict help-seeking among 2016–2018 pregnancy risk assessment monitoring system participants with postpartum depression symptoms*. Women's Health. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9685210/

Appendices

Data Set:

PPD_source_data

Data Pre-processing Code:

```
#Importing the necesaary libraries
import pandas as pd
import numpy as np
Original Dataset

#Reading the original dataset
data = pd.read_csv('/content/drive/MyDrive/DAB304/post natal data.csv')
data.head()
#Getting the basic information about the data
data.info()
#Dropping the timestamp column from the dataset
data = data.drop('Timestamp', axis=1)
data.columns
#Getting a basic idea of the dataset
data.describe()
Data Augmentation using Bootstrapping

# Number of bootstrap samples to generate
n_bootstrap_samples = 100

# Creating an empty DataFrame to store bootstrapped samples
bootstrapped_data = pd.DataFrame()

# Performing bootstrapping
for _ in range(n_bootstrap_samples):
    # Sample with replacement from the original DataFrame
    bootstrap_sample = data.sample(n=len(data), replace=True)
    # Append the bootstrapped sample to the bootstrapped_data DataFrame
    bootstrapped_data = bootstrapped_data.append(bootstrap_sample, ignore_index=True)

# Printing the shape of the bootstrapped data to verify the increase in the number of
records
print("Shape of bootstrapped data:", bootstrapped_data.shape)
#Checking all the columns in the dataset
bootstrapped.columns
Data Processing for Visualization

# Counting missing values in each column
missing_values_count = bootstrapped.isna().sum()
```

```
# Printing the count of missing values
print("Count of missing values in each column:")
print(missing_values_count)
# Converting categorical columns to object type
for col in bootstrapped.select_dtypes(include='category').columns:
    bootstrapped[col] = bootstrapped[col].astype('object')

# Filling missing values with "Not Shared"
bootstrapped_data = bootstrapped.fillna("Unknown")

# Printing the filled DataFrame
bootstrapped_data.info()
# Check for missing values in bootstrapped_data
bootstrapped_data.isna().sum()
bootstrapped_data = bootstrapped_data.drop(['Timestamp'], axis=1)
bootstrapped_data.head()
#Creating 'patient_id' column
bootstrapped_data['patient_id'] = bootstrapped_data.index + 1
bootstrapped_data.head()
# bootstrapped_data = bootstrapped_data[['patient_id'] + [col for col in
bootstrapped_data.columns if col != 'patient_id']]
bootstrapped_data.shape
bootstrapped_data.tail()
bootstrapped_data.iloc[-1]
# Saving the bootstrapped data to a CSV file
bootstrapped.to_csv('bootstrapped.csv', index=False)

bootstrapped.to_csv('path/bootstrapped.csv', index=False)
Data Processing for Machine Learning

#Replacing the spaces with '_' in column names
column_rename_mapping = {
    'Feeling sad or Tearful': 'Feeling_sad_or_Tearful',
    'Irritable towards baby & partner': 'Irritable_towards_baby_&_partner',
    'Trouble sleeping at night': 'Trouble_sleeping_at_night',
    'Problems concentrating or making decision':
'Problems_concentrating_or_making_decision',
    'Overeating or loss of appetite': 'Overeating_or_loss_of_appetite',
    'Feeling anxious': 'Feeling_anxious',
    'Feeling of guilt': 'Feeling_of_guilt',
    'Problems of bonding with baby': 'Problems_of_bonding_with_baby',
    'Suicide attempt': 'Suicide_attempt'
}

# Renaming columns using the rename() function
bootstrapped_data.rename(columns=column_rename_mapping, inplace=True)
bootstrapped_data.describe()
data_bs = pd.read_csv('/file_path/bstrapped_data.csv')
data_bs.head()
from sklearn.preprocessing import LabelEncoder
```

```
# Creating a copy of the DataFrame
encoded_df = data_bs.copy()

# One-hot encode all columns except the target column
encoded_df = pd.get_dummies(encoded_df, columns=[col for col in encoded_df.columns if col
!= 'Suicide attempt'])

# Initialize LabelEncoder for the target column
label_encoder = LabelEncoder()

# Encode the target column
encoded_df['Suicide attempt'] = label_encoder.fit_transform(encoded_df['Suicide
attempt'])

# Print the encoded DataFrame
print(encoded_df)
##Checking for Supervised Classifier Models compatible with our Dataset

!pip install lazypredict
from lazypredict.Supervised import LazyClassifier

# Dropping non-numeric columns
X = encoded_df.drop(['Suicide_attempt'], axis=1)
y = encoded_df['Suicide_attempt']

# # Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# # Initializing LazyClassifier
clsfier = LazyClassifier(verbose=0, ignore_warnings=True, custom_metric=None)

# # Fit LazyClassifier
models, predictions = clsfier.fit(X_train, X_test, y_train, y_test)

# # Print model performance
print(models)
```

Machine Learning Code:

```
Model to be Used at the Backend of UI
import pandas as pd
import numpy as np
data_bs = pd.read_csv('bootstrapped_data.csv')
data_bs.head()
data_bs.isna().sum()
lbl_enc = data_bs.copy()
lbl_enc.isna().sum()
```

```python
lbl_enc.dropna(inplace=True)
lbl_enc.isna().sum()
# Define the mapping for the target column
mapping_1 = {'Yes': 2, 'No': 0, 'Not interested to say': 1}
mapping_2 = {'Yes': 2, 'No': 0, 'Sometimes': 1}
mapping_3 = {'Yes': 2, 'No': 0, 'Maybe': 1}
mapping_4 = {'Yes': 1, 'No': 0}
mapping_5 = {'Yes': 2, 'No': 1, 'Not at all': 0}
mapping_6 = {'Yes': 1, 'No': 0, 'Often': 2}
mapping_7 = {'Two or more days a week': 2, 'No': 0, 'Yes': 1}
mapping_8 = {'Yes': 2, 'No': 0, 'Sometimes' : 1}
mapping_9 = {'Yes': 2, 'No': 0, 'Sometimes' : 1}
mapping_10 = {'25-30': 0, '30-35': 1, '35-40' : 2, '40-45' : 3, '45-50' : 4}

# Apply the mapping to the target column
lbl_enc['Suicide_attempt'] = lbl_enc['Suicide_attempt'].map(mapping_1)
lbl_enc['Problems_of_bonding_with_baby'] =
lbl_enc['Problems_of_bonding_with_baby'].map(mapping_2)
lbl_enc['Feeling_of_guilt'] = lbl_enc['Feeling_of_guilt'].map(mapping_3)
lbl_enc['Feeling_anxious'] = lbl_enc['Feeling_anxious'].map(mapping_4)
lbl_enc['Overeating_or_loss_of_appetite'] =
lbl_enc['Overeating_or_loss_of_appetite'].map(mapping_5)
lbl_enc['Problems_concentrating_or_making_decision'] =
lbl_enc['Problems_concentrating_or_making_decision'].map(mapping_6)
lbl_enc['Trouble_sleeping_at_night'] =
lbl_enc['Trouble_sleeping_at_night'].map(mapping_7)
lbl_enc['Irritable_towards_baby_&_partner'] =
lbl_enc['Irritable_towards_baby_&_partner'].map(mapping_8)
lbl_enc['Feeling_sad_or_Tearful'] = lbl_enc['Feeling_sad_or_Tearful'].map(mapping_9)
lbl_enc['Age'] = lbl_enc['Age'].map(mapping_10)

# Print the encoded DataFrame
lbl_enc.head()
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Dropping non-numeric columns
X = lbl_enc.drop(['Suicide_attempt'], axis=1)
y = lbl_enc['Suicide_attempt']

# # Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(random_state=42)

# Train the classifier
rf_classifier.fit(X_train, y_train)

# Predict on the test set
```

```
y_pred = rf_classifier.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
X_new_test = pd.read_csv("New_data.csv")
# Replace spaces with underscores in column names
X_new_test.rename(columns=lambda x: x.replace(' ', '_'), inplace=True)

# Display the updated DataFrame with modified column names
X_new_test.head()
# X_final = pd.get_dummies(X_new_test, dtype =  int)
X_new_test.columns
# Define the mapping for the target column
# mapping_1 = {'Yes': 2, 'No': 0, 'Not interested to say': 1}
mapping_2 = {'Yes': 2, 'No': 0, 'Sometimes': 1}
mapping_3 = {'Yes': 2, 'No': 0, 'Maybe': 1}
mapping_4 = {'Yes': 1, 'No': 0}
mapping_5 = {'Yes': 2, 'No': 1, 'Not at all': 0}
mapping_6 = {'Yes': 1, 'No': 0, 'Often': 2}
mapping_7 = {'Two or more days a week': 2, 'No': 0, 'Yes': 1}
mapping_8 = {'Yes': 2, 'No': 0, 'Sometimes' : 1}
mapping_9 = {'Yes': 2, 'No': 0, 'Sometimes' : 1}
mapping_10 = {'25-30': 0, '30-35': 1, '35-40' : 2, '40-45' : 3, '45-50' : 4}

# Apply the mapping to the target column
# X_new_test['Suicide_attempt'] = X_new_test['Suicide_attempt'].map(mapping_1)
X_new_test['Problems_of_bonding_with_baby'] =
X_new_test['Problems_of_bonding_with_baby'].map(mapping_2)
X_new_test['Feeling_of_guilt'] = X_new_test['Feeling_of_guilt'].map(mapping_3)
X_new_test['Feeling_anxious'] = X_new_test['Feeling_anxious'].map(mapping_4)
X_new_test['Overeating_or_loss_of_appetite'] =
X_new_test['Overeating_or_loss_of_appetite'].map(mapping_5)
X_new_test['Problems_concentrating_or_making_decision'] =
X_new_test['Problems_concentrating_or_making_decision'].map(mapping_6)
X_new_test['Trouble_sleeping_at_night'] =
X_new_test['Trouble_sleeping_at_night'].map(mapping_7)
X_new_test['Irritable_towards_baby_&_partner'] =
X_new_test['Irritable_towards_baby_&_partner'].map(mapping_8)
X_new_test['Feeling_sad_or_Tearful'] =
X_new_test['Feeling_sad_or_Tearful'].map(mapping_9)
X_new_test['Age'] = X_new_test['Age'].map(mapping_10)

# Print the encoded DataFrame
X_new_test.head()
rf_classifier.predict(X_new_test)
import joblib

# Serialize (saving) the trained model to a file
joblib.dump(rf_classifier, 'random_forest_model.pkl')
```

App.py Code:

```
Model Deployment

!pip install Flask
from flask import Flask, request, render_template
import joblib
import pandas as pd
import numpy as np
import pandas as pd
import flask
from flask import request
import joblib  # Assuming you saved your machine learning model using joblib

# Load your trained machine learning model
model = joblib.load(open('random_forest_model.pkl','rb'))

app = flask.Flask(__name__, template_folder='templates', static_folder='static')

@app.route('/')
def main():
    return(flask.render_template('main.html'))

@app.route('/predict', methods=['POST'])
def predict():

   # Parsing the input data from the request and appending it to the DataFrame
    Age = request.form['Age']
    Feeling_sad_or_Tearful = request.form['Feeling_sad_or_Tearful']
    Irritable_towards_baby_partner = request.form['Irritable_towards_baby_&_partner']
    Trouble_sleeping_at_night = request.form['Trouble_sleeping_at_night']
    Problems_concentrating_or_making_decision =
request.form['Problems_concentrating_or_making_decision']
    Overeating_or_loss_of_appetite = request.form['Overeating_or_loss_of_appetite']
    Feeling_anxious = request.form['Feeling_anxious']
    Feeling_of_guilt = request.form['Feeling_of_guilt']
    Problems_of_bonding_with_baby = request.form['Problems_of_bonding_with_baby']

    df = pd.DataFrame({'Age': [Age],
                    'Feeling_sad_or_Tearful': [Feeling_sad_or_Tearful],
                    'Irritable_towards_baby_&_partner': [Irritable_towards_baby_partner],
                    'Trouble_sleeping_at_night': [Trouble_sleeping_at_night],
                    'Problems_concentrating_or_making_decision':
[Problems_concentrating_or_making_decision],
                    'Overeating_or_loss_of_appetite': [Overeating_or_loss_of_appetite],
                    'Feeling_anxious': [Feeling_anxious],
                    'Feeling_of_guilt': [Feeling_of_guilt],
                   'Problems_of_bonding_with_baby': [Problems_of_bonding_with_baby]})


    mapping_2 = {'Yes': 2, 'No': 0, 'Sometimes': 1}
```

```
    mapping_3 = {'Yes': 2, 'No': 0, 'Maybe': 1}
    mapping_4 = {'Yes': 1, 'No': 0}
    mapping_5 = {'Yes': 2, 'No': 1, 'Not at all': 0}
    mapping_6 = {'Yes': 1, 'No': 0, 'Often': 2}
    mapping_7 = {'Two or more days a week': 2, 'No': 0, 'Yes': 1}
    mapping_8 = {'Yes': 2, 'No': 0, 'Sometimes' : 1}
    mapping_9 = {'Yes': 2, 'No': 0, 'Sometimes' : 1}
    mapping_10 = {'25-30': 0, '30-35': 1, '35-40' : 2, '40-45' : 3, '45-50' : 4}

    # Applying the mapping
    # df['Suicide_attempt'] = df['Suicide_attempt'].map(mapping_1)
    df['Problems_of_bonding_with_baby'] =
df['Problems_of_bonding_with_baby'].map(mapping_2)
    df['Feeling_of_guilt'] = df['Feeling_of_guilt'].map(mapping_3)
    df['Feeling_anxious'] = df['Feeling_anxious'].map(mapping_4)
    df['Overeating_or_loss_of_appetite'] =
df['Overeating_or_loss_of_appetite'].map(mapping_5)
    df['Problems_concentrating_or_making_decision'] =
df['Problems_concentrating_or_making_decision'].map(mapping_6)
    df['Trouble_sleeping_at_night'] = df['Trouble_sleeping_at_night'].map(mapping_7)
    df['Irritable_towards_baby_&_partner'] =
df['Irritable_towards_baby_&_partner'].map(mapping_8)
    df['Feeling_sad_or_Tearful'] = df['Feeling_sad_or_Tearful'].map(mapping_9)
    df['Age'] = df['Age'].map(mapping_10)

    # Making predictions using the loaded model and the data stored in the DataFrame
    prediction = model.predict(df)

    #Values to be returned on making predictions
    label_mapping = {
    0: "There is NO indication of suicidal thought or attempts.",
    1: "The patient is LIKELY to have suicidal thoughts or has plans of committing one.",
    2: "The patient is EXTREMELY LIKELY to have suicidal thoughts or has plans of
committing one."
    }
    predicted_label = label_mapping.get(prediction[0], "Unknown")

    # Returning prediction result as plain text
    return flask.render_template('main.html', prediction=predicted_label)

if __name__ == '__main__':
    app.run(debug=True, use_reloader=False)
```

Html Web Page:

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <style>
        body {
            font-family: Arial, sans-serif;
            text-align: left;
            background-image: url('/static/postpartum.jpg');
            background-position: center;
            background-size: auto;
            background-repeat: no-repeat;
            margin: 0; /* Remove default margin */
            padding: 0; /* Remove default padding */
            height: 100vh; /* Set height of viewport */
        }

        h1 {
            text-align: center;
            color: maroon; /* Maroon color for heading */
            font-weight: bold; /* Bold font weight for heading */
            margin-top: 3px; /* Adjust margin-top of h1 */
            margin-bottom: 9px; /* Adjust margin-bottom of h1 */
        }

        .container {
            display: flex;
            justify-content: center;
            align-items: center;
        }

        form {
            margin: auto;
            width: 80%; /* Adjust width to fit the screen */
            max-width: 650px; /* Set maximum width */
            background-color: rgba(255, 255, 255, 0.7); /* White color with 50% opacity
*/
            padding: 20px;
            border-radius: 10px;
            box-shadow: 0 4px 8px rgba(0, 0, 0, 0.1); /* Add shadow effect */
            border: 2px solid #ccc; /* Grey border */
            overflow: hidden; /* Hide overflow */
            margin-bottom:0;
        }

        label {
            display: block;
            margin-bottom: 10px;
```

```
    font-weight: bold; /* Make labels bold */
}

select {
    width: calc(100% - 20px); /* Adjust width of selects */
    font-weight: bold;
    background-color: rgba(255, 255, 255, 0.5);
    padding: 5px; /* Reduce padding */
    margin-bottom: 29px; /* Reduce margin-bottom */
    border: 1px solid #ccc;
    border-radius: 4px;
    box-sizing: content-box;
}

.button-container {
    display: flex;
    justify-content: space-between;
    margin-top: 0px;
    margin-bottom: 0px;
}

button {
    background-color: #b59c8a;
    color: black;
    padding: 10px 20px;
    border: 1px solid #333; /* Adding border */
    border-radius: 4px;
    cursor: pointer;
    width: calc(50% - 5px); /* Adjust width to fit both buttons */
    font-weight: bold; /* Make buttons bold */
}

button:hover {
    background-color: #d6c9c6;
}


.result-container {
    position: absolute; /* Position result container absolutely */
    top: 45%; /* Align result container to top of form container */
    right: 150px;  /*Position result container to the right */
    width: 250px; /* Set width of result container */
}

.result {
    text-align: center; /* Align result text to the left */
    margin-left: 20px; /* Adjust margin as needed */
    width: 130%; /* Adjust the width as needed */
    padding: 20px;
    border: 2px solid #333; /* Add black border */
    border-radius: 10px; /* Add border radius for rounded corners */
```

```
            background-color: rgba(255, 255, 255, 0.4);
            font-weight: bold;
        }

        h2 {
            color: maroon; /* Maroon color for heading */
            font-weight: bold; /* Bold font weight for heading */
            margin-top: 0px; /* Adjust margin-top of h1 */
            margin-bottom: 1px; /* Adjust margin-bottom of h1 */
        }
    </style>
</head>
</body>
    <h1>Postpartum Depression</h1>
    <div class="container">
    <form action="/predict" method="post">
        <label for="Age">What is the Age of the Patient?</label>
        <select id="Age" name="Age" required>
            <option value="" disabled selected>Choose One</option>
            <option value="25-30">25-30</option>
            <option value="30-35">30-35</option>
            <option value="35-40">35-40</option>
            <option value="40-45">40-45</option>
            <option value="45-50">45-50</option>
        </select>
        <br>
        <label for="Feeling_sad_or_Tearful">Is the Patient Feeling Sad or
Tearful?</label>
        <select id="Feeling_sad_or_Tearful" name="Feeling_sad_or_Tearful" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="Sometimes">Sometimes</option>
            <option value="No">No</option>
        </select>
        <br>
        <label for="Irritable_towards_baby_&_partner">Does the Patient get Irritable
Towards Baby &/or her Partner?</label>
        <select id="Irritable_towards_baby_&_partner"
name="Irritable_towards_baby_&_partner" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="Sometimes">Sometimes</option>
            <option value="No">No</option>
        </select>
        <br>
        <label for="Trouble_sleeping_at_night">Does the patient have any Trouble Sleeping
at Night?</label>
        <select id="Trouble_sleeping_at_night" name="Trouble_sleeping_at_night" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="Two or more days a week">Two or More Days a Week</option>
```

```
            <option value="No">No</option>
        </select>
        <br>
        <label for="Problems_concentrating_or_making_decision">Is the patient Facing Problems Concentrating or Making Decisions?</label>
        <select id="Problems_concentrating_or_making_decision" name="Problems_concentrating_or_making_decision" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="Often">Often</option>
            <option value="No">No</option>
        </select>
        <br>
        <label for="Overeating_or_loss_of_appetite">Is the Patient Overeating or feeling the Loss of Appetite?</label>
        <select id="Overeating_or_loss_of_appetite" name="Overeating_or_loss_of_appetite" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="No">No</option>
            <option value="Not at all">Not At All</option>
        </select>
        <br>
        <label for="Feeling_anxious">Is the patient Feeling Anxious?</label>
        <select id="Feeling_anxious" name="Feeling_anxious" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="No">No</option>
        </select>
        <br>
        <label for="Feeling_of_guilt">Is the patient Feeling Guilty?</label>
        <select id="Feeling_of_guilt" name="Feeling_of_guilt" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="Maybe">Maybe</option>
            <option value="No">No</option>
        </select>
        <br>
        <label for="Problems_of_bonding_with_baby">Is the patient having Problems Bonding with Baby?</label>
        <select id="Problems_of_bonding_with_baby" name="Problems_of_bonding_with_baby" required>
            <option value="" disabled selected>Choose One</option>
            <option value="Yes">Yes</option>
            <option value="Sometimes">Sometimes</option>
            <option value="No">No</option>
        </select>
        <br>
        <button type="submit" onclick="predict()">PREDICT</button>
        <button type="reset" value="Reset">RESET</button>
    </form>
```

```
    <div class="result-container">
    {% if prediction %}
    <div class="result">
        <h2>Prediction Result:</h2>
            <p>According to the patient's current response: {{ prediction }}</p>
    </div>
    {% endif %}
    </div>
</body>
</html>
```