# Sentiment Analysis for Mental Health Monitoring

Jasser Abdelfattah Mohammed SRN: 21033101

#### Abstract

Mental health is a critical concern, especially among students. This project aims to develop a binary classification model for sentiment analysis, evaluating mental health status based on textual data. The model classifies entries as either "normal" or "abnormal". This paper discusses the dataset, preprocessing steps, model development, and results.

#### 1 Problem Statement

Undiagnosed mental health issues can lead to severe consequences, particularly for students. The objective of this project is to create a sentiment analysis model to evaluate mental health statuses using textual data like tweets or posts. The model categorizes entries into:

- Normal
- Abnormal (e.g., depression, anxiety, stress)

This system can enable schools to identify students requiring mental health support proactively.

## 2 Dataset Description

#### 2.1 Data Overview

The dataset contains textual statements related to mental health, labeled with one of seven categories:

- Normal
- Depression
- Suicidal
- Anxiety
- Stress
- Bipolar Disorder

• Personality Disorder

#### 2.2 Data Sources

The data originates from social media platforms such as Twitter and Reddit. Preprocessing ensures its relevance and accuracy. This dataset is suited for:

- Training intelligent mental health chatbots.
- Conducting sentiment analysis.
- Exploring mental health trends.

#### 2.3 Key Features

- unique\_id: Unique identifier for each entry.
- Statement: The textual content of the post.
- Mental Health Status: Annotated mental health status of the statement.

### 3 Approach Explanation

#### 3.1 Data Preprocessing

- Cleaning: Removed noise, special characters, and irrelevant data.
- Tokenization: Split text into smaller tokens for analysis.

### 3.2 Exploratory Data Analysis (EDA)

- Analyzed class distribution for balanced representation.
- Created word clouds to visualize common terms.

### 3.3 Feature Engineering

Mapped mental health statuses into two classes:

- Normal
- Abnormal

Text features were extracted using:

- Bag-of-Words (BoW)
- TF-IDF (Term Frequency-Inverse Document Frequency)

#### 3.4 Model Building

Implemented and trained two models:

Naive Bayes

#### • Logistic Regression

#### 3.5 Model Evaluation

Evaluated using:

- Metrics: Precision, recall, F1-score, and accuracy.
- Performance was assessed on a held-out test dataset.

### 4 Results and Discussion

### 4.1 Naive Bayes Model Results

• Confusion Matrix:

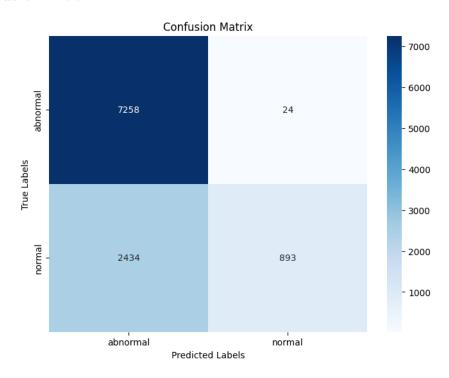


Figure 1: Naive Bayes Confusion Matrix

#### • Classification Report:

Classification	Report: precision	recall	f1-score	support
abnormal	0.75	1.00	0.86	7282
normal	0.97	0.27	0.42	3327
				40500
accuracy			0.77	10609
macro avg	0.86	0.63	0.64	10609
weighted avg	0.82	0.77	0.72	10609

Figure 2: Naive Bayes Classification Report

Accuracy: 77%

### 4.2 Logistic Regression Model Results

#### • Confusion Matrix:

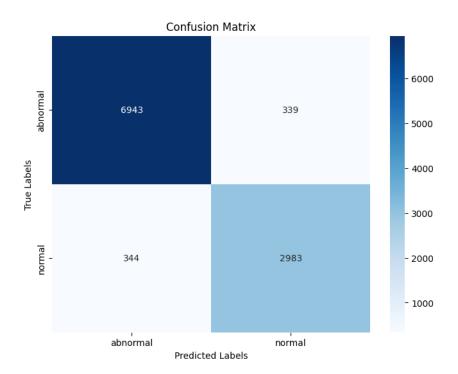


Figure 3: Logistic Regression Confusion Matrix

#### • Classification Report:

Classification		11	£4	
	precision	recall	f1-score	support
abnormal	0.95	0.95	0.95	7282
normal	0.90	0.90	0.90	3327
accuracy			0.94	10609
macro avg	0.93	0.93	0.93	10609
weighted avg	0.94	0.94	0.94	10609

Figure 4: Logistic Regression Classification Report

Accuracy: 94%

### 5 Performance on Unseen Data

This section evaluates the performance of the models on unseen data.

#### 5.1 Naive Bayes Model Predictions

```
Post: I feel like my heart is racing, and I can't catch my breath.

Prediction: abnormal

Post: One moment I'm laughing uncontrollably, and the next I'm crying for no reason.

Prediction: abnormal

Post: Nothing excites me anymore, and even getting out of bed feels like a chore.

Prediction: abnormal

Post: I had a great day at work and treated myself to some ice cream afterward!

Prediction: normal

Post: Sometimes I feel like I'm living someone else's life, and it's confusing.

Prediction: abnormal

Post: The constant deadlines are crushing me; I can't keep up.

Prediction: abnormal

Post: No one would even notice if I disappeared.

Prediction: abnormal
```

Figure 5: Naive Bayes Model Predictions on Unseen Data

#### 5.2 Logistic Regression Model Predictions

```
Post: I feel like my heart is racing, and I can't catch my breath.

Prediction: normal

Post: One moment I'm laughing uncontrollably, and the next I'm crying for no reason.

Prediction: normal

Post: Nothing excites me anymore, and even getting out of bed feels like a chore.

Prediction: abnormal

Post: I had a great day at work and treated myself to some ice cream afterward!

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Post: Sometimes I feel like I'm living someone else's life, and it's confusing.

Prediction: abnormal

Post: The constant deadlines are crushing me; I can't keep up.

Prediction: normal

Post: No one would even notice if I disappeared.

Prediction: normal
```

Figure 6: Logistic Regression Model Predictions on Unseen Data

# 6 Conclusion and Next Steps

The Logistic Regression model outperformed Naive Bayes with higher accuracy but bad unseen data predictions. However, both models exhibited unique strengths:

• Naive Bayes: Achieved Better performance on unseen data which means its a better Model overall.

• Logistic Regression: Achieved Greater accuracy but was not successful in detecting unseen data correctly as Naive Bayes .

### 6.1 Future Work

- 1. Incorporate Transformer Models (e.g., BERT, RoBERTa).
- 2. Explore hybrid model combinations.