Sentiment Analysis for Mental Health Monitoring 🤯

Sentiment Analysis for Mental Health Monitoring 🤯

> [dataset source](#) 📎

About The Datset 🖇️

This comprehensive dataset is a meticulously curated collection of mental health statuses tagged from various statements. The dataset amalgamates raw data from multiple sources, cleaned and compiled to create a robust resource for developing chatbots and performing sentiment analysis.

Data Souce 🌍

The dataset integrates information from the following Kaggle datasets:

- 3k Conversations Dataset for Chatbot
- Depression Reddit Cleaned
- Human Stress Prediction
- Predicting Anxiety in Mental Health Data
- Mental Health Dataset Bipolar
- Reddit Mental Health Data
- Students Anxiety and Depression Dataset
- Suicidal Mental Health Dataset

- Suicidal Tweet Detection Dataset

Datset Over View :

- **Description:**

  This dataset is a comprehensive collection of 50,000 text statements related to mental health, each tagged with one of seven mental health statuses. The primary purpose of this dataset is to assist in building machine learning models for classifying mental health conditions based on textual data, such as social media posts or other user-generated content.

- **Columns:**

  1. **unique_id**: A unique identifier for each entry.
  2. **statement**: A piece of text, typically a statement or comment, associated with a particular mental health status.
  3. **status**: The mental health status assigned to the statement. The possible categories are:
     - Normal
     - Depression
     - Suicidal
     - Anxiety
     - Stress
     - Bi-Polar
     - Personality Disorder

Usage :

This dataset is ideal for training machine learning models aimed at understanding and predicting mental health conditions based on textual data. It can be used in various applications such as:

- Chatbot development for mental health support.
- Sentiment analysis to gauge mental health trends.
-

How we use NLP Concepts

In our text processing methodology, we begin by removing punctuation, URLs, and hyperlinks from the statements. Additionally, we eliminate stop words, such as "is," "are," and "the," to enhance the focus on more informative terms.

In the realm of morphological analysis, we extract the stems of the words. Subsequently, we employ a TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer to transform the processed text into a vector representation. This vector is then utilized to fit the mode

---

Conlusion

in the conclusion we train and tune a four model wich is :

- SVM
- Logistic Regression
- Neural Ntwork
- KNN the first three give a Convergent results with accuracy near to 76 % , and the last one give a 65 % acc .

Double-click (or enter) to edit

Two Level Classification Approach

About Two-Level Classification

In a two-level classification approach, we break down a multi-class classification problem into two stages:

1. **Stage 1 - Binary Classification**:
   - This stage first classifies data into two categories: **Normal** ans **Non-Normal**.
   - By creating this separation, we simplify the problem and reduce the initial complexity, allowing the model to focus on distinguishing between these high-level classes.
   - This binary classifier uses features from the full dataset, ensuring that it can accurately detect if a statement falls into the "Normal" or "Non-Normal" category.
2. **Stage 2 - Multi-Class Classification**:
   - In this stage, we take statements classified as **Non-Normal** from Stage 1 and further classify them into specific mental health categories such as **Depression**, **Suicidal**, **Anxiety**, **Stress**, **Bi-Polar**, and **Personality Disorder**.
   - This multi-class classifier uses data that has already been identified as "Non-Normal," focusing on differentiating among various mental health conditions.

Why Two-Level Classification?

- 🌵**Improved Accuracy**: This approach allows each classifier to focus on a subset of the problem, potentially increasing accuracy by reducing the complexity each model has to handle.
- 🍀 **Efficient Use of Resources**: By filtering out "Normal" cases in Stage 1, Stage 2 can concentrate only on differentiating among the specific mental health conditions, making it more efficient.
- 🧿 **Handling Imbalance**: Many datasets are imbalanced, with "Normal" cases being more common. Splitting the classification into two levels allows us to address class imbalance in each level separately.

How It Works in This Model

1. **Data Preparation**:
   - First, we preprocess the dataset by cleaning the text and extracting features (e.g., TF-IDF, POS tags, emojis).
   - Then, we split the data for training and testing each stage separately.
2. **Training**:
   - **Stage 1**: We train a binary classifier on the full training data to classify statements as **Normal** or **Non-Normal**.
   - **Stage 2**: We train a multi-class classifier on the subset of training data labeled as **Non-Normal**, focusing only on the six specific mental health conditions.
3. **Testing**:
   - For each test instance, we first use Stage 1 to determine if it's "Normal" or "Non-Normal."
   - If classified as **Non-Normal**, the instance is passed to Stage 2, where it is classified into one of the specific mental health categories.

Evaluation and Metrics

- **Stage-Specific Metrics**: Each stage is evaluated separately, with accuracy, recall, precision, and F1-score measured for both the binary and multi-class classifiers.
- **Combined Evaluation**: Finally, we combine predictions from both stages to evaluate the overall performance of the two-level classification system.

This two-level approach allows us to accurately identify both "Normal" and specific mental health conditions, leveraging targeted classification strategies to improve overall accuracy and interpretability.

Dataset Loading and Preparing

Import Libraries :

---

lets start by importing the nessacary libraries

[ ] ↳ 3 cells hidden

Loading the dataset

```
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
df = pd.read_csv('/content/drive/MyDrive/CombinedData.csv', index_col=0)
```

```
df.head(3)
```

	statement	status
0	oh my gosh	Anxiety
1	trouble sleeping, confused mind, restless hear...	Anxiety
2	All wrong, back off dear, forward doubt. Stay ...	Anxiety

Next steps: View recommended plots New interactive sheet

notes1: as we se at first , we have a three column the id which we should drop it, the statment that represent the "input" and the output which is the status. so our problem is just a classification and we need to make a nlp pre processing to extract feature as we can from the statment to make them as input to the model.

note2: as we say, also we wil add some statistical feature (test len) to nlp extracted features.

some random example :

- to see the statement how itis

```
# Group by status and get a random statement from each group
random_statements = df.groupby('status')['statement'].apply(lambda x: x.sample(n=1).iloc[0])

# Print the results
for status, statement in random_statements.items():
    print(f"Status: {status}\n")
    print(f"Statement: {statement}\n")
    print("-----------------------------------")
```

```
Status: Anxiety

Statement: A reminder that progress isn't linear and that's okay! I felt like my anxiety had gotten worse lately and that I had gone bac

Take care x

-----------------------------------
Status: Bipolar

Statement: Is lithium *making* me manic or did I forget what good feels like? I have a new doc, and at the same time, new insurance that

And I feel great! I'd been in a depressive episode for two weeks and that is out the window. I've been more productive this week than th

Am I overreacting? Or is this the start of mania? The thing that's got me a little bugged out is that while I used to wake up groggy and

Also unrelated, but what do you lithium folks do about pain? I used to take 800mg ibprofen for my migraine and now I can't. Tylenol has

-----------------------------------
Status: Depression

Statement: I am gaming with my cousin every evening but hes is making fun off me and trashtalking me recently more and more Especially w

-----------------------------------
Status: Normal

Statement: Koncoku looks smart, but why don't you know how to win the NBA po Serie A?

-----------------------------------
Status: Personality disorder
```

```
Statement: AvPD diagnosed recently Hey all, I was diagnosed with AvPD quite recently (and finally I guess) after all those years spent i

-----------------------------------
Status: Stress

Statement: Stress Management Stress is an inevitable part of life. It can be caused by a variety of factors, such as work pressures, fin

[https://beautyaal.com/stress-management/](https://beautyaal.com/stress-management/)

-----------------------------------
Status: Suicidal

Statement: So I am aware that mostly these posts do not get much attention and I am not going to cry for help or whatever else. Would th

-----------------------------------
```

Data set Descriping and statistics

```
df.describe()
```

	statement	status
count	52681	53043
unique	51073	7
top	what do you mean?	Normal
freq	22	16351

Missings Value Removal

```
df.isna().sum()
```

	0
statement	362
status	0

dtype: int64

```
df.dropna(inplace = True)
df.isna().sum()
```

	0
statement	0
status	0

dtype: int64

What is our Labels 'target'?

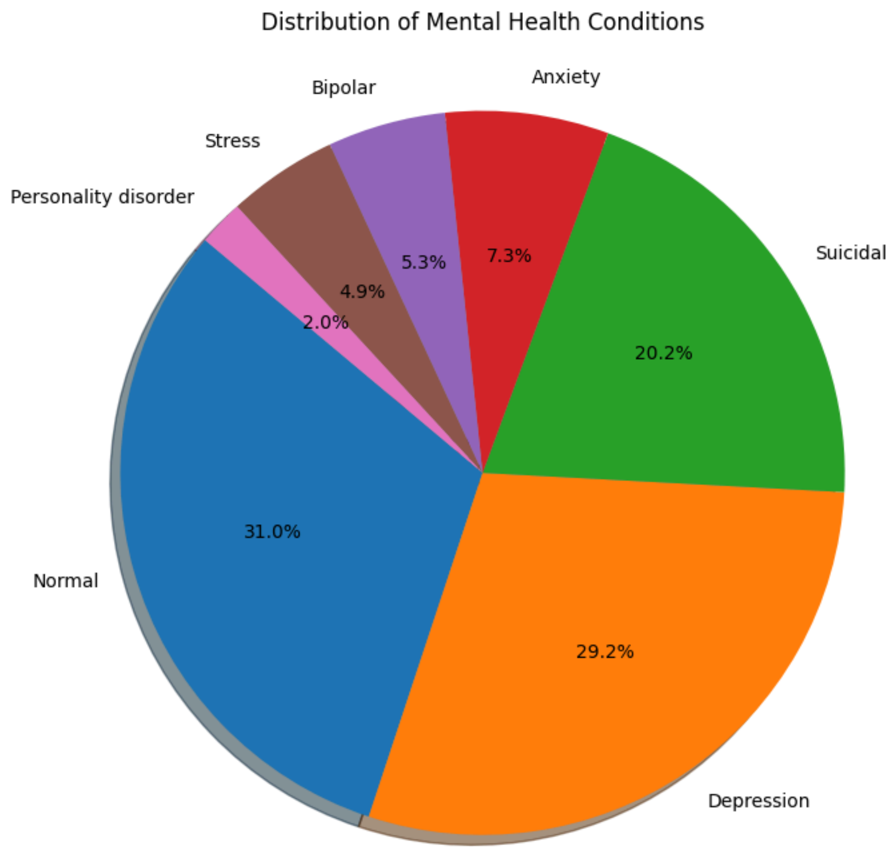
```
df['status'].unique()
```

```
array(['Anxiety', 'Normal', 'Depression', 'Suicidal', 'Stress', 'Bipolar',
       'Personality disorder'], dtype=object)
```

How the samples are distributed over the status ?

```
# Count the occurrences of each category
status_counts = df['status'].value_counts()

# Define colors for each category (7 colors for 7 categories)
```

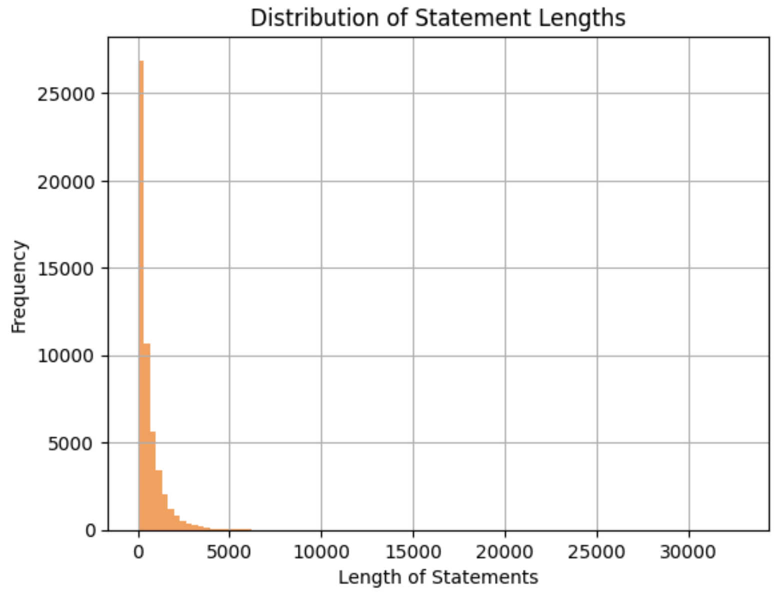
```
colors = ['#1F77B4', '#FF7F0E', '#2CA02C', '#D62728', '#9467BD', '#8C564B', '#E377C2']

# Create the pie chart
plt.figure(figsize=(7, 7))
plt.pie(status_counts, labels=status_counts.index, autopct='%1.1f%%',
        startangle=140, colors=colors, shadow=True)

plt.title('Distribution of Mental Health Conditions')
plt.axis('equal')

# Display the chart
plt.tight_layout()
plt.show()
```



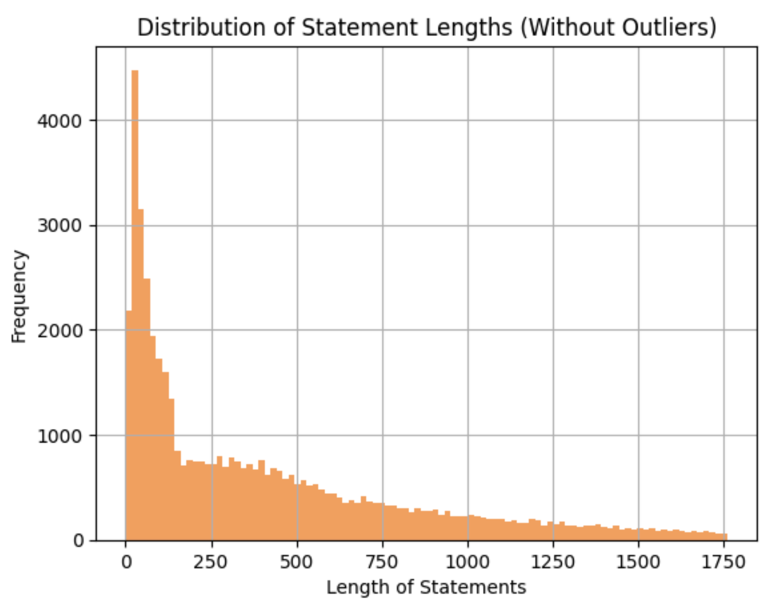
How the statements length are distibuted?

```
# calculate the length of each statement
df['statemnent_length'] = df['statement'].str.len()
```

```
# plot the distribution of statement lengths
df['statemnent_length'].hist(bins=100, color='#F4A261')
plt.title('Distribution of Statement Lengths')
plt.xlabel('Length of Statements')
plt.ylabel('Frequency')
plt.show()
```




```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = df['statemnent_length'].quantile(0.25)
Q3 = df['statemnent_length'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bound for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR


# Filter out the outliers
filtered_df = df[(df['statemnent_length'] >= lower_bound) & (df['statemnent_length'] <= upper_bound)]
# Plot the distribution of statement lengths without outliers
filtered_df['statemnent_length'].hist(bins=100, color='#F4A261')
plt.title('Distribution of Statement Lengths (Without Outliers)')
plt.xlabel('Length of Statements')
plt.ylabel('Frequency')
plt.show()
```



```
nltk.download('stopwords')
nltk.download('punkt')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
True
```

🐈 *NLP Pre-Processing*

what we will do

---

in this part of the ml pipeline, we perform several essential NLP preprocessing steps to prepare our data for machine learning. These steps include:

1. **Text Processing:**
   - include :
     - pattern reomving (links,emails and etc.)
     - lower casing
     - stop words removing
2. **tokinezation & Stemming :**
   - Tokenization :
     - this step converts each text sample into an array of tokens (individual words or sub-words).
     - we use Stanza word tokenizer to ensure precise, language-specific tokenization.
   - Stemming :
     - in this step, we transform each tokenized array into a stemmed version, reducing each word to its base or root form.
     - stanza NLP tools allow us to use various stemming techniques for extracting meaningful root words.
3. **Part-of-Speech (POS) Tagging and Filtering**:

- sing Stanza, we apply POS tagging to identify and filter specific parts of speech, such as:
  - **Verbs**: Identify and include only verbs to capture action-related semantics.
  - **Nouns**: Extract nouns to focus on entity- or object-based information.
  - **Adjectives**: Include adjectives to analyze descriptive language and sentiment.
- This POS filtering allows us to tailor the input data by emphasizing different linguistic elements and can be customized based on the classification or NLP goals.

1. Text Processing:

1.1 Lower casing

[ ] ↳ *1 cell hidden*

1.2 Special Patterns Removing

here we define our function to remoe the speacial paterns which is :

1. links
2. emails
3. markdown text
4. handles
5. puctuation

```
def remove_patterns(text):

    # remove URL's
    text = re.sub(r'http[s]?://\S+', '', text)

    # remove markdown-style links
    text = re.sub(r'\[.*?\]\(.*?\)', '', text)

    # remove handles (that start with '@')
    text = re.sub(r'@\w+', '', text)

    # remove punctuation and other special characters
    text = re.sub(r'[^\w\s]', '', text)
    return text.strip()
```

aplying the special patterns removing

```
# apply the function to the statements
df['statement'] = df['statement'].apply(remove_patterns)
```

1.3 Remove Stop words

```
stop_words = set(stopwords.words('english'))

def remove_stopwords(text):
    words = text.split()
    filtered_words = [word for word in words if word not in stop_words]
    return " ".join(filtered_words)
```

```
# df['statement'] = df['statement'].apply(remove_stopwords)
```

1.4 Emoji-features Extractions

Convert smiles to words

```
# Function to convert emojis and emoticons to descriptive text
def convert_emojis(text):
    emoticon_map = {
        r':\)+': 'happy_face',
        r':D+': 'very_happy_face',
        r':\(+': 'sad_face',
        r':\'\(+': 'crying_face',
        r';\)+': 'winking_face',
        r':O': 'surprised_face',
        r'>:\(+': 'angry_face',
        r':\|': 'neutral_face',
        r'<3': 'heart',
        r'B-\)+': 'cool_face'
    }
    for emoticon, replacement in emoticon_map.items():
```

```
        text = re.sub(emoticon, replacement, text)
    text = emoji.demojize(text, delimiters=("", ""))
    return text
```

text of emojies only

```
import re

# Define the emoticon map with patterns and corresponding labels
emoticon_map = {
    r':\)+': 'happy_face',
    r':D+': 'very_happy_face',
    r':\(+': 'sad_face',
    r':\'\(+': 'crying_face',
    r';\)+': 'winking_face',
    r':O': 'surprised_face',
    r'>:\(+': 'angry_face',
    r':\|': 'neutral_face',
    r'<3': 'heart',
    r'B-\)+': 'cool_face'
}

# Function to extract emoticons and replace with descriptive labels
def extract_emojis(text):
    emoji_labels = []
    for pattern, label in emoticon_map.items():
        matches = re.findall(pattern, text)
        emoji_labels.extend([label] * len(matches))  # Add label for each matched emoticon
    return ' '.join(emoji_labels)  # Join labels into a single string

# Example usage
text = "I'm so happy :) and winking ;) with a heart <3"
print(extract_emojis(text))  # Output: "happy_face winking_face heart"
```

```
happy_face winking_face heart
```

apply the emoji converter

```
# Apply emoji conversion to the 'statement' column
df['statement_with_emojis'] = df['statement'].apply(convert_emojis)
df['statement'] = df['statement'].apply(convert_emojis)
```

emojies bar chart

```
from collections import Counter

# Split the emoji labels into individual words and flatten the list
all_emojis = ' '.join(df['statement_with_emojis']).split()  # Flatten all labels into a single list

# Count occurrences of each emoji label
emoji_counts = Counter(all_emojis)
emoji_counts_df = pd.DataFrame(emoji_counts.items(), columns=['Emoji', 'Count'])
```

```
emoji_counts_df
```

	Emoji	Count
0	oh	970
1	my	119437
2	gosh	44
3	trouble	564
4	sleeping	904
...	...	...
77347	coprophobia	1
77348	strokelike	1
77349	attacklike	1
77350	tingeling	1
77351	fatherdaughter	1

77352 rows × 2 columns

Next steps: View recommended plots New interactive sheet

```
# import seaborn as sns
# import matplotlib.pyplot as plt

# # Set up the plot
# plt.figure(figsize=(12, 8))
# sns.heatmap(emoticon_counts, annot=True, fmt="d", cmap="YlGnBu", cbar_kws={'label': 'Frequency'})

# # Add titles and labels
# plt.title("Distribution of Emoticons by Mental Health Status")
# plt.xlabel("Emoticon (Symbol and Description)")
# plt.ylabel("Mental Health Status")
# plt.xticks(rotation=45, ha="right")
# plt.tight_layout()
# plt.show()
```

1.5 Slang Converting

Define the set of slang

```
# Define a custom slang dictionary
slang_dict = {
    "idk": "I don't know",
    "omg": "oh my god",
    "rn": "right now",
    "brb": "be right back",
    "tbh": "to be honest",
    "ikr": "I know, right",
    "smh": "shaking my head",
    "lol": "laughing out loud",
    "lmao": "laughing my ass off",
    "rofl": "rolling on the floor laughing",
    "afaik": "as far as I know",
    "idc": "I don't care",
    "np": "no problem",
    "fyi": "for your information",
    "imo": "in my opinion",
    "pls": "please",
    "thx": "thanks",
    "w/": "with",
    "b4": "before",
    "bc": "because",
    "gr8": "great",
    "btwn": "between",
    "cya": "see you",
    "ty": "thank you",
    "bday": "birthday",
```

```
}
```

Define the expanding functino

```
changes = 0  # Count how many words are expanded
```

```
# Function to expand slang terms based on the custom dictionary
def expand_slang(text):
    words = text.split()
    expanded_words = []
    global changes
    for word in words:
        # Check if the word is in the slang dictionary
        expanded_word = slang_dict.get(word.lower(), word)
        if word.lower() in slang_dict:
            changes=changes+ 1  # Increment count if a word was expanded
        expanded_words.append(expanded_word)

    return ' '.join(expanded_words)
```

Apply the expanding

```
# Apply the slang expansion function to the 'statement' column
df['statement'] = df['statement'].apply(expand_slang)
```

```
print(f"Total number of slang words expanded across all rows: {changes}")
```

```
Total number of slang words expanded across all rows: 4525
```

2.Tokenization & Stemming

Intialize Stanza Piplein

[ ] ↳ *1 cell hidden*

2.1 Tokenization

How the sentences frequency is ?

```
# Calculate the number of sentences for each statement
df['num_of_sentences'] = df['statement'].apply(sentence_tokenize)

df.sample(5)  # Display a sample of the DataFrame
```

	statement	status	statemnent_length	statement_with_emojis	num_of_sentences
47727	im just tired i dont know why im even sad but ...	Depression	129	im just tired i dont know why im even sad but...	[im just tired i dont know why im even sad but...
7521	it is been along time and i have litterally be...	Suicidal	299	it is been along time and i have litterally be...	[it is been along time and i have litterally b...
2899	this is so big boy	Normal	18	this is so big boy	[this is so big boy]
20557	i feel so safe in this subreddit i do not even...	Suicidal	1793	i feel so safe in this subreddit i do not even...	[i feel so safe in this subreddit i do not eve...
9462	what if you are just going deeper	Suicidal	100	what if you are just going deeper and	[what if you are just going deeper

bar chart for the num f scentences and its frequency

Words tokenization

define word tokenizing funcyion

```
nltk.download('punkt')

def extract_tokens(text):
    # Tokenize the text into words using NLTK
    words = nltk.word_tokenize(text)
    return words
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

apply extract tokenz function

```
# apply word tokenize to each element in the statements
df['tokens'] = df['statement'].apply(extract_tokens)
```

Sample after tokenizing

```
df.sample(2)
```

	statement	status	statemnent_length	statement_with_emojis	num_of_sentences	tokens
3251	i already told mom if you want to order it in ...	Normal	284	i already told mom if you want to order it in ...	[i already told mom if you want to order it in...	[i, already, told, mom, if, you, want, to, ord...
10035	life is fucking shit allways has been i have h...	Suicidal	191	life is fucking shit allways has been i have h...	[life is fucking shit allways has been i have ...	[life, is, fucking, shit, allways, has, been, ...

2.2 Stemming

Intializing the steemer

[ ] ↳ *1 cell hidden*

Apply the stemming Function

```
df['tokens_stemmed'] = df['tokens'].apply(tokens_stem)
```

Sample

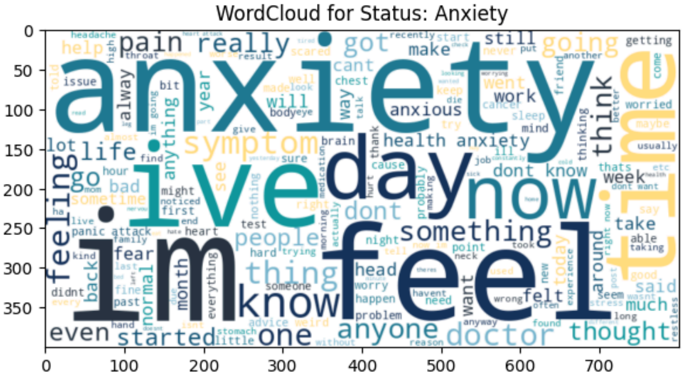
```
# Display sample of the DataFrame
df.sample(5)
```

	statement	status	statemnent_length	statement_with_emojis	num_of_sentences	tokens	tokens_stemmed
52716	did i have a panic attack about a month ago i ...	Anxiety	3623	did i have a panic attack about a month ago i ...	[did i have a panic attack about a month ago i...	[did, i, have, a, panic, attack, about, a, mon...	did i have a panic attack about a month ago i ...
41166	we re out of the bundus god complex stage of d...	Depression	70	we re out of the bundus god complex stage of d...	[we re out of the bundus god complex stage of ...	[we, re, out, of, the, bundus, god, complex, s...	we re out of the bundus god complex stage of d...
49290	looking for participants to use a mobile app d...	Stress	3101	looking for participants to use a mobile app d...	[looking for participants to use a mobile app ...	[looking, for, participants, to, use, a, mobil...	look for particip to use a mobil app design fo...
25644	now that i am planing my way to end my life i ...	Depression	455	now that i am planing my way to end my life i ...	[now that i am planing my way to end my life i...	[now, that, i, am, planing, my, way, to, end. ...	now that i am plane my way to end my life i ki...

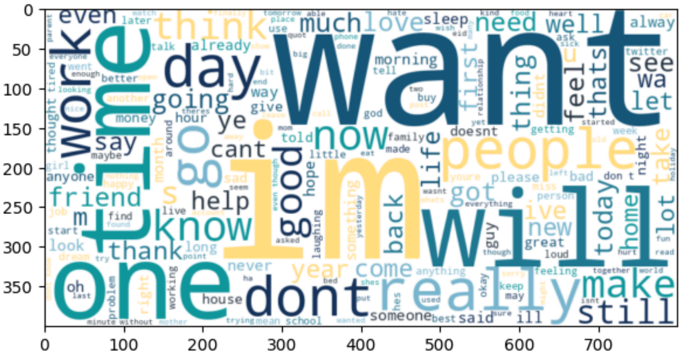
2.3 word counts

```
colors = ['#16325B', '#227B94', '#78B7D0', '#FFDC7F', '#18587A', '#11999E', '#283644']

# Define a color function
def color_func(word, font_size, position, orientation, random_state=101, **kwargs):
    return random.choice(colors)


statuses = df['status'].unique()

plt.figure(figsize=(12, 36))  # Adjust figure size as needed

# Generate and plot the WordCloud for each category
for i, status in enumerate(statuses):
    # Filter the tokens data for the current status
    tokens_data = ' '.join(df[df['status'] == status]['tokens'].dropna().apply(lambda x: ' '.join(x)).tolist())

    # Generate the WordCloud
    wordcloud = WordCloud(width=800, height=400, background_color='white', color_func=color_func).generate(tokens_data)

    # Plot the WordCloud in a subplot
    axes = plt.subplot(len(statuses) // 2 + 1, 2, i + 1)  # Adjust number of rows and columns dynamically
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f'WordCloud for Status: {status}')
    #plt.axis('off')  # Turn off axes for a cleaner look

# Apply tight layout after generating all subplots
plt.tight_layout()

# Adjust the vertical spacing between subplots (hspace controls vertical space)
plt.subplots_adjust(hspace= -0.8)
plt.show()
```

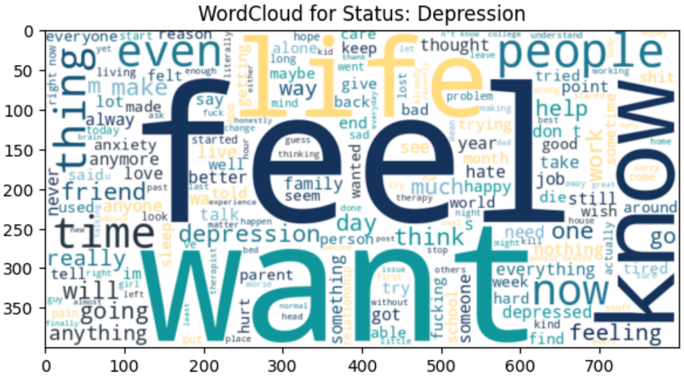
WordCloud for Status: Anxiety



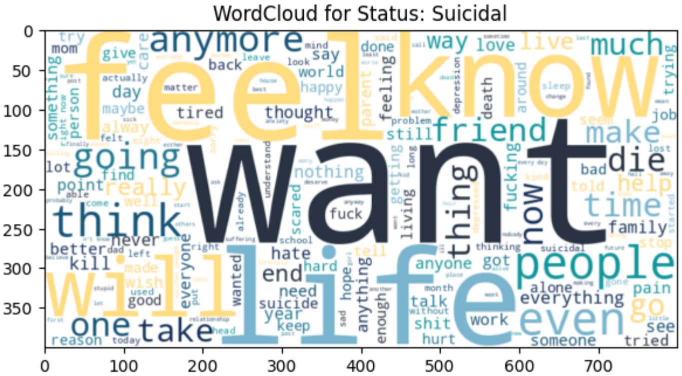
WordCloud for Status: Normal



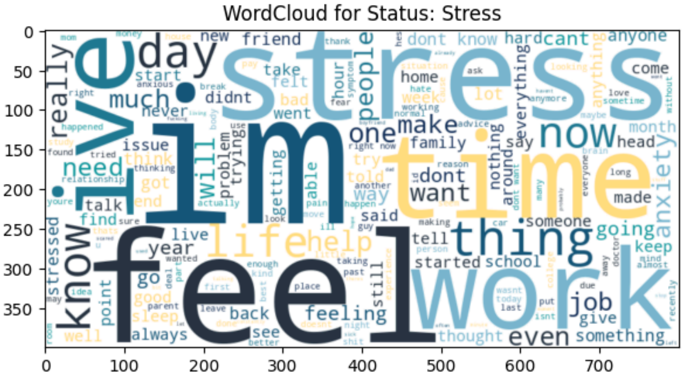
WordCloud for Status: Depression



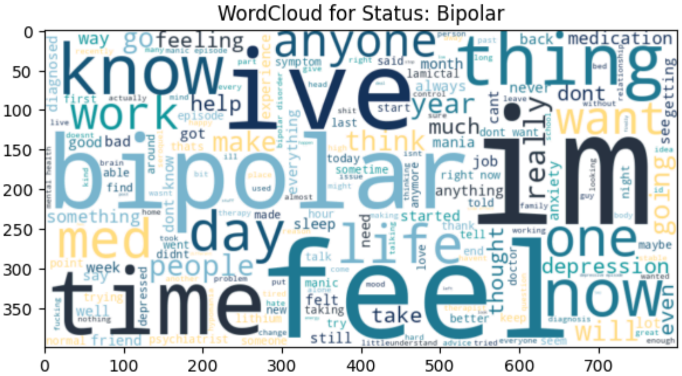
WordCloud for Status: Suicidal



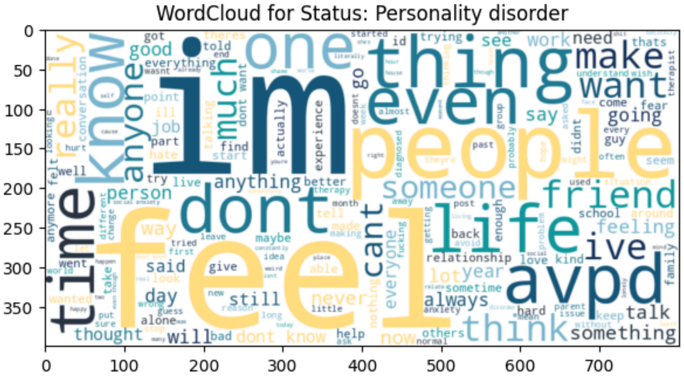
WordCloud for Status: Stress



WordCloud for Status: Bipolar



WordCloud for Status: Personality disorder



3. Part-Of-Speach (POS) Tagging

3.1 Extract POS Taggs

Nlp

[ ] ↳ *2 cells hidden*

define function to extract pos

```
import nltk

def extract_pos_tokens(text, pos_tag_prefix):
    # Tokenize the input text
    tokens = nltk.word_tokenize(text)
    # Get the POS tags
    pos_tags = nltk.pos_tag(tokens)

    # Extract tokens based on POS tag prefix
    tokens_filtered = [word for word, pos in pos_tags if pos.startswith(pos_tag_prefix)]

    return ' '.join(tokens_filtered)
```

Extract Verbs

```
df['tokens_verbs'] = df['statement'].apply(lambda x: extract_pos_tokens(x, 'V'))
```

Extract Nouns

```
df['tokens_nouns'] = df['statement'].apply(lambda x: extract_pos_tokens(x, 'N'))
```

Extrac Adjectives

```
df['tokens_adj'] = df['statement'].apply(lambda x: extract_pos_tokens(x, 'J'))
```

Sample

```
df.sample(2)
```

	statement	status	statemnent_length	statement_with_emojis	num_of_sentences	tokens	tokens_stemmed	tokens_verbs	tokens_nc
34439	im convinced i may have blood clots in my leg ...	Anxiety	2699	im convinced i may have blood clots in my leg ...	[im convinced i may have blood clots in my leg...	[im, convinced, i, may, have, blood, clots, in...	im convinc i may have blood clot in my leg at ...	convinced have caved was sleeping woke realize...	im i b clots leg week spring b
3242	president director lee tina is successful	Normal	72	president director lee tina is successful who ...	[president director lee tina is successful who...	[president, director, lee, tina, is, successfu	presid director lee tina is success who pay to	is pays be	presi director presi

Vectorizing using TF-IDF

About VEctorizing Approach

What is the TF (Term of Frequency) and IDF (Inverse Document Frequency)?

- **What is TF-IDF?**

TF-IDF (Term Frequency-Inverse Document Frequency) is a numerical statistic used to evaluate the importance of a word in a document relative to a collection of documents, typically in the context of text mining and Natural Language Processing (NLP). It is commonly used as a feature extraction method to convert textual data into numerical features that machine learning models can process.

- The TF-IDF measure combines two components:

1. **Term Frequency (TF):**

   Definition: The number of times a word (term) appears in a document, divided by the total number of words in that document. It gives us a sense of how important a word is within a single document.

   Formula:

$$\text{TF}(t,d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}$$

2. **Inverse Document Frequency (IDF):**

   Definition: The logarithm of the total number of documents in the corpus divided by the number of documents containing the term.

   It measures how important a word is across the whole corpus. Common words that appear in many documents (like "the," "is") have low IDF values because they are less informative, while rare terms have higher IDF values.

   Formula:

$$\text{IDF}(t,D) = \log\left(\frac{\text{Total number of documents in the corpus}}{1 + \text{Number of documents containing the term } t}\right)$$

3. **TF-IDF:**

   Definition: The product of the term frequency (TF) and inverse document frequency (IDF) for a term in a document. It reflects both the term's frequency within a specific document and how unique or important the term is across the entire document corpus.

   Formula:

$$\text{TF-IDF}(t,d,D) = \text{TF}(t,d) \times \text{IDF}(t,D)$$

   In these formulas:

   - (t) refers to a term (word),
   - (d) refers to a document,
   - (D) refers to the entire corpus (collection of documents),
   - (\log) is the logarithm function, typically base 10 or natural logarithm.

- **How TF-IDF is Useful Feature Extraction in NLP:** TF-IDF helps convert raw text data into a matrix of numerical features, making the data suitable for machine learning models. Each document is represented as a vector of TF-IDF values, where each value corresponds to the importance of a word in that document. This is a common technique in text classification tasks, such as sentiment analysis, spam detection, and topic classification.

  Captures the Importance of Words: By using TF-IDF, we can ignore frequently occurring but uninformative words (e.g., "the", "and") and focus on more meaningful terms that are key to the context of a document. This helps improve the accuracy and relevance of the model's predictions by emphasizing words that differentiate one document from another.

  Reduces Noise in Text: TF-IDF reduces the weight of very common words across all documents, as they are often not useful for distinguishing between documents. It assigns higher importance to rare and meaningful terms, which tend to carry more information about the content of the document.

  Improves Text Similarity Measures: TF-IDF vectors are often used to calculate the similarity between documents (e.g., using cosine similarity). This is useful in tasks like document clustering, search engines, and recommendation systems.

- **Use Case in Mental Health Sentiment Analysis**

  In our dataset, which contains mental health-related statements, applying TF-IDF can help the model understand which words are most significant for predicting the mental health status of a given statement. For example:

  - Words like "hopeless," "depressed," and "suicidal" may have high TF-IDF scores in documents labeled with "Depression" or "Suicidal" mental health statuses, but these words may be rare across other categories.
    - Common words like "I," "the," and "is" will have low IDF values since they appear in many documents, making them less useful for classification.

  By transforming the text data into TF-IDF vectors, you provide a more informative and compact representation of the statements, which can lead to better performance of machine learning models.

Initialize separate TF-IDF Vectorizer

Initialize separate TF-IDF Vectorizer for verbs and nouns and adj , stemm

```
vectorizer_emojis = TfidfVectorizer(max_features=100, stop_words='english')

vectorizer_stemmes = TfidfVectorizer(ngram_range=(1, 2), max_features=2000, stop_words='english')

vectorizer_verbs = TfidfVectorizer(ngram_range=(1, 2), max_features=500, stop_words='english')

vectorizer_nouns = TfidfVectorizer(ngram_range=(1, 2), max_features=500, stop_words='english')

vectorizer_adjectives = TfidfVectorizer(ngram_range=(1, 2), max_features=500, stop_words='english')
```

Extract Verb, Nouuns , ... Vectors

Emojies

```
# Emojis

X_emojis_tfidf = vectorizer_emojis.fit_transform(df['statement_with_emojis'])
```

stemmes

```
# Adjectives
X_stemm_tfidf = vectorizer_stemmes.fit_transform(df['tokens_stemmed'].astype(str))
```

verbs

```
# Verbs

X_verbs_tfidf = vectorizer_verbs.fit_transform(df['tokens_verbs'].astype(str))
```

nouns

```
# Nouns

X_nouns_tfidf = vectorizer_nouns.fit_transform(df['tokens_nouns'].astype(str))
```

Adjectives

```
# Adjectives

X_adjectives_tfidf = vectorizer_adjectives.fit_transform(df['tokens_adj'].astype(str))
```

comdine Vectors

[ ] ↳ *1 cell hidden*

Dataset Spliting, Encoding and Staging

```
from sklearn.model_selection import train_test_split

# Split the vectorized data into train and test sets
X_train_full, X_test, y_train_full, y_test = train_test_split(X_combined_tfidf, df['status'], test_size=0.2, random_state=42)
```

Encode LAbles and slpit status

Encode LAbles

```
# Encode labels for binary classification (Stage 1)
binary_encoder = LabelEncoder()
y_train_full_binary = binary_encoder.fit_transform(y_train_full.apply(lambda x: 'Normal' if x == 'Normal' else 'Non-Normal'))
y_test_binary = binary_encoder.transform(y_test.apply(lambda x: 'Normal' if x == 'Normal' else 'Non-Normal'))

# Encode labels for multi-class classification (Stage 2)
multi_encoder = LabelEncoder()
y_train_full_multi = multi_encoder.fit_transform(y_train_full[y_train_full != 'Normal'])  # Only for "Non-Normal" classes
y_test_multi = multi_encoder.transform(y_test[y_test != 'Normal'])  # Only for "Non-Normal" classes
```

split to Stages

```
# Split train data for Stage 1 and Stage 2
X_train_tfidf_stage1 = X_train_full
X_train_tfidf_stage2 = X_train_full[y_train_full != 'Normal']
y_train_tfidf_stage1 = y_train_full_binary
y_train_tfidf_stage2 = y_train_full_multi

X_test_tfidf_stage1 = X_test
X_test_tfidf_stage2 = X_test[y_test != 'Normal']
```

OverSampling using SMOTE

```
# Apply SMOTE for oversampling on Stage 2
smote = SMOTE(random_state=42)

X_train_tfidf_stage2, y_train_stage2 = smote.fit_resample(X_train_tfidf_stage2, y_train_tfidf_stage2)
#X_train_tfidf_stage1, y_train_stage1 = smote.fit_resample(X_train_tfidf_stage1, y_train_tfidf_stage1)
```

Normal Statement Classification

What we will do

> Stage 1
>
> 1.1 Logistic regression classifier
>
> 2.2 neural network classifier
>
> 2.3 chosssing the best classifier

1.1 Stage 1: Logistic Regression

Grid Search Param Definie

```
# Define the binary classifier
clf = LogisticRegression(max_iter=1000, random_state=42)

# Define the parameter grid for GridSearchCV
param_grid = {
    'C': [0.01, 0.1, 0.8,1,2, 10, 100],  # Regularization strength
    'solver': ['lbfgs', 'liblinear'],  # Optimization algorithms
    'penalty': ['l2'],  # Regularization type
}
```

Grid Search Fit

```
# Perform Grid Search with cross-validation
grid_search = GridSearchCV(clf, param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train_tfidf_stage1, y_train_tfidf_stage1)
```

```
GridSearchCV
best_estimator_: LogisticRegression
LogisticRegression
```

best PArarms

```
# Get the best parameters and accuracy
best_params = grid_search.best_params_
best_accuracy = grid_search.best_score_

print(f"Best parameters: {best_params}")
print(f"Best accuracy: {best_accuracy}")
```

```
Best parameters: {'C': 1, 'penalty': 'l2', 'solver': 'lbfgs'}
Best accuracy: 0.9417472775611442
```

```
svm_classifier= SVC(random_state=42)
#svm_classifier.fit(X_train_tfidf_stage1, y_train_stage1)
```

```
logistic1_classifier= grid_search.best_estimator_
```

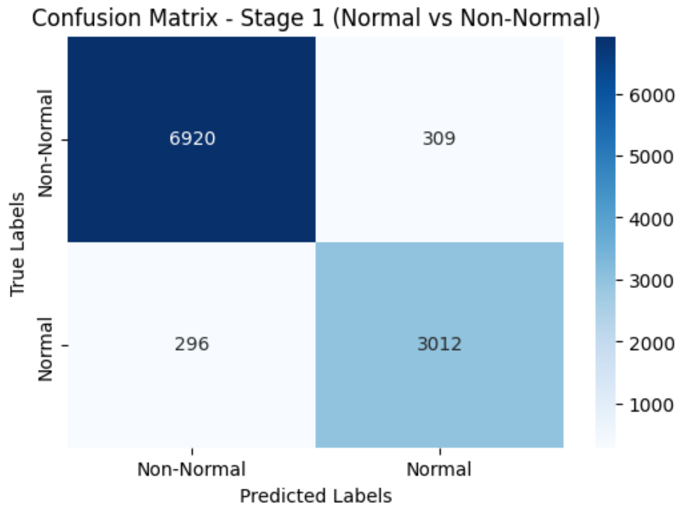
classification report

```
# Evaluate binary classifier
y_pred_stage1 = logistic1_classifier.predict(X_test_tfidf_stage1)
print("Stage 1 (Binary Classification) - Normal vs Non-Normal")
print("Accuracy:", accuracy_score(y_test_binary, y_pred_stage1))
print(classification_report(y_test_binary, y_pred_stage1))
print("Confusion Matrix:\n", confusion_matrix(y_test_binary, y_pred_stage1))
```

```
Stage 1 (Binary Classification) - Normal vs Non-Normal
Accuracy: 0.9425832779728576
              precision    recall  f1-score   support

           0       0.96      0.96      0.96      7229
           1       0.91      0.91      0.91      3308

    accuracy                           0.94     10537
   macro avg       0.93      0.93      0.93     10537
weighted avg       0.94      0.94      0.94     10537

Confusion Matrix:
 [[6920  309]
 [ 296 3012]]
```

Heat Map

```
# Calculate confusion matrix for Stage 1
conf_matrix_stage1 = confusion_matrix(y_test_binary, y_pred_stage1)

# Plot heatmap for Stage 1
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_stage1, annot=True, fmt="d", cmap="Blues", xticklabels=binary_encoder.classes_, yticklabels=binary_encoder.classes_)
plt.title("Confusion Matrix - Stage 1 (Normal vs Non-Normal)")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```



1.2 Stage 1: Neural Network

Neural Network Layers

```
# Define the layers in an array
layers = [
    Dense(units=256, activation='relu', input_shape=(X_train_tfidf_stage1.shape[1],),kernel_regularizer=l2(0.01)),  # Input Layer
    BatchNormalization(),
    Dropout(rate=0.2),  # Dropout Layer 1
    Dense(units=64, activation='relu',kernel_regularizer=l2(0.01)),  # Hidden Layer 1
    Dropout(rate=0.1),  # Dropout Layer 1
    Dense(units=16, activation='relu',kernel_regularizer=l2(0.01)),  # Hidden Layer 2

    Dense(units=2, activation='softmax')  # Output Layer
]

# Initialize the Sequential model
model = Sequential(layers)


# Compile the model: Using Adam optimizer, sparse categorical crossentropy loss, and accuracy as the metric
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Model Training

```
# Train the model on training data with validation on the test data
history = model.fit(X_train_tfidf_stage1.toarray(),
                    y_train_tfidf_stage1,
                    epochs=20,
                    batch_size=64,
                    validation_split=0.3
                    )
```

```
Epoch 1/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 13s 24ms/step - accuracy: 0.8819 - loss: 2.3918 - val_accuracy: 0.8916 - val_loss: 0.5478
Epoch 2/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 23ms/step - accuracy: 0.9294 - loss: 0.4073 - val_accuracy: 0.9224 - val_loss: 0.3505
Epoch 3/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 11s 23ms/step - accuracy: 0.9278 - loss: 0.3346 - val_accuracy: 0.9281 - val_loss: 0.3144
Epoch 4/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 22ms/step - accuracy: 0.9321 - loss: 0.3084 - val_accuracy: 0.9269 - val_loss: 0.3081
Epoch 5/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 21s 23ms/step - accuracy: 0.9372 - loss: 0.2871 - val_accuracy: 0.9311 - val_loss: 0.2966
```

```
Epoch 6/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 22ms/step - accuracy: 0.9404 - loss: 0.2631 - val_accuracy: 0.9310 - val_loss: 0.2800
Epoch 7/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 19s 20ms/step - accuracy: 0.9419 - loss: 0.2580 - val_accuracy: 0.9330 - val_loss: 0.2700
Epoch 8/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 10s 22ms/step - accuracy: 0.9438 - loss: 0.2492 - val_accuracy: 0.9316 - val_loss: 0.2771
Epoch 9/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 11s 23ms/step - accuracy: 0.9471 - loss: 0.2416 - val_accuracy: 0.9338 - val_loss: 0.2691
Epoch 10/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 22ms/step - accuracy: 0.9432 - loss: 0.2469 - val_accuracy: 0.9340 - val_loss: 0.2667
Epoch 11/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 11s 23ms/step - accuracy: 0.9470 - loss: 0.2352 - val_accuracy: 0.9344 - val_loss: 0.2626
Epoch 12/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 21ms/step - accuracy: 0.9435 - loss: 0.2399 - val_accuracy: 0.9313 - val_loss: 0.2775
Epoch 13/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 11s 24ms/step - accuracy: 0.9447 - loss: 0.2355 - val_accuracy: 0.9309 - val_loss: 0.2737
Epoch 14/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 22ms/step - accuracy: 0.9459 - loss: 0.2317 - val_accuracy: 0.9306 - val_loss: 0.2702
Epoch 15/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 11s 23ms/step - accuracy: 0.9473 - loss: 0.2289 - val_accuracy: 0.9321 - val_loss: 0.2663
Epoch 16/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 20s 22ms/step - accuracy: 0.9504 - loss: 0.2249 - val_accuracy: 0.9307 - val_loss: 0.2652
Epoch 17/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 11s 23ms/step - accuracy: 0.9466 - loss: 0.2290 - val_accuracy: 0.9313 - val_loss: 0.2662
Epoch 18/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 21s 23ms/step - accuracy: 0.9480 - loss: 0.2275 - val_accuracy: 0.9332 - val_loss: 0.2623
Epoch 19/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 19s 21ms/step - accuracy: 0.9472 - loss: 0.2287 - val_accuracy: 0.9332 - val_loss: 0.2712
Epoch 20/20
461/461 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - accuracy: 0.9483 - loss: 0.2272 - val_accuracy: 0.9330 - val_loss: 0.2625
```

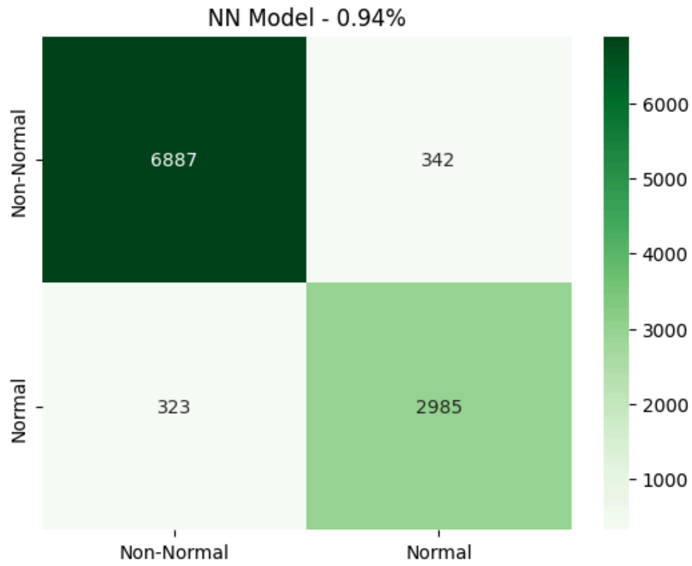
Confusion Matrix

```
# Make predictions on the test set
y_pred_prob = model.predict(X_test_tfidf_stage1.toarray())
y_pred = y_pred_prob.argmax(axis=1)  # Convert probabilities to class predictions

# Calculate the accuracy
accuracy_nn = accuracy_score(y_test_binary,y_pred)
print("\n")
print("Accuracy:", accuracy_nn)

# Compute the confusion matrix

conf_matrix_nn = confusion_matrix(y_test_binary,y_pred)

# Print classification report
print("Confusion Matrix:\n", confusion_matrix(y_test_binary,y_pred))
print(classification_report(y_test_binary, y_pred_stage1))
```

```
330/330 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step


Accuracy: 0.9368890576065294
Confusion Matrix:
 [[6887  342]
 [ 323 2985]]
```

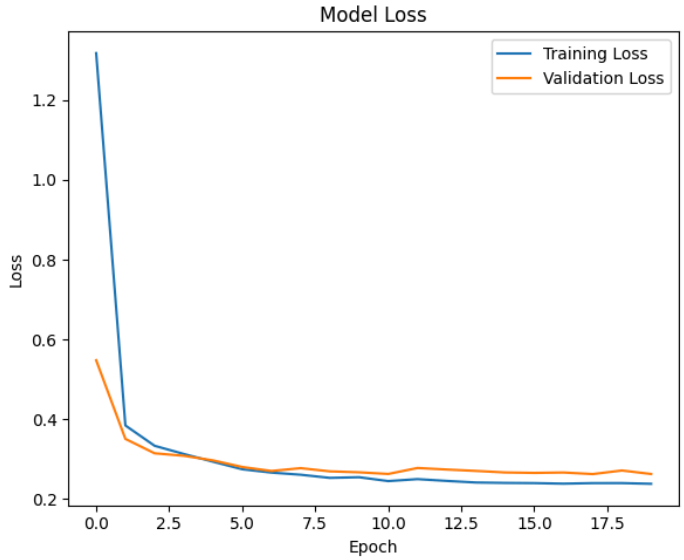
Heat Map

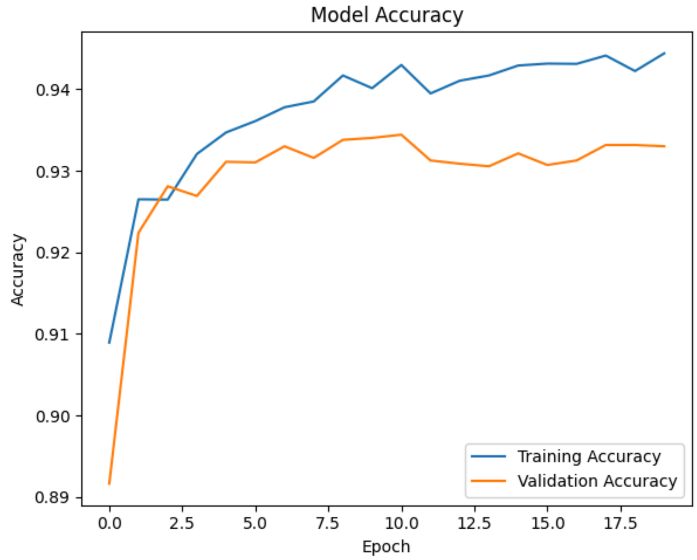
```
ax = sns.heatmap(conf_matrix_nn, annot = True, fmt='d', cmap='Greens', xticklabels=binary_encoder.classes_, yticklabels=binary_encoder.class
ax.set_title(f'NN Model - {accuracy_nn:.2}%')
plt.show()
```



Model Loss and Accuracy

```
plt.figure(figsize=(12, 5))

# Plot training & validation loss values
plt.subplot(1, 2, 1)  # 1 row, 2 columns, 1st subplot
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')

# Plot training & validation accuracy values
plt.subplot(1, 2, 2)  # 1 row, 2 columns, 2nd subplot
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

plt.tight_layout()  # Adjusts subplots to fit in the figure area.
plt.show()  # Display the plots
```





1.3 Best Classifier for Stage 1

we chose the best classfier for this stage

```
binary_classifier = logistic1_classifier
```

Non Normal Statement Classification

2.1 logistic Regression Stage 2

Grid Search Params

```
# Define the binary classifier
clf = LogisticRegression(max_iter=1000, random_state=42)

# Define the parameter grid for GridSearchCV
param_grid = {
    'C': [ 0.03,0.01, 0.02],  # Regularization strength
    'solver': ['lbfgs'],  # Optimization algorithms
    'penalty': ['l2'],  # Regularization type
}

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=clf, param_grid=param_grid, scoring='accuracy', cv=5, n_jobs=-1, verbose=1)
```

Train the Model

```
# Fit the grid search on the training data
grid_search.fit(X_train_tfidf_stage2, y_train_stage2)
```

```
Fitting 5 folds for each of 3 candidates, totalling 15 fits
GridSearchCV
best_estimator_: LogisticRegression
LogisticRegression
```

Best Classifier

```
# Get the best model and hyperparameters
best_clf = grid_search.best_estimator_
print("Best hyperparameters found: ", grid_search.best_params_)
```

```
Best hyperparameters found:  {'C': 0.03, 'penalty': 'l2', 'solver': 'lbfgs'}
```

```
# Train multi-class classifier for Stage 2
logistic_classifier =best_clf
#multi_classifier = SVC(random_state=42,kernel='poly')

# multi_classifier.fit(X_train_tfidf_stage2, y_train_stage2)
```

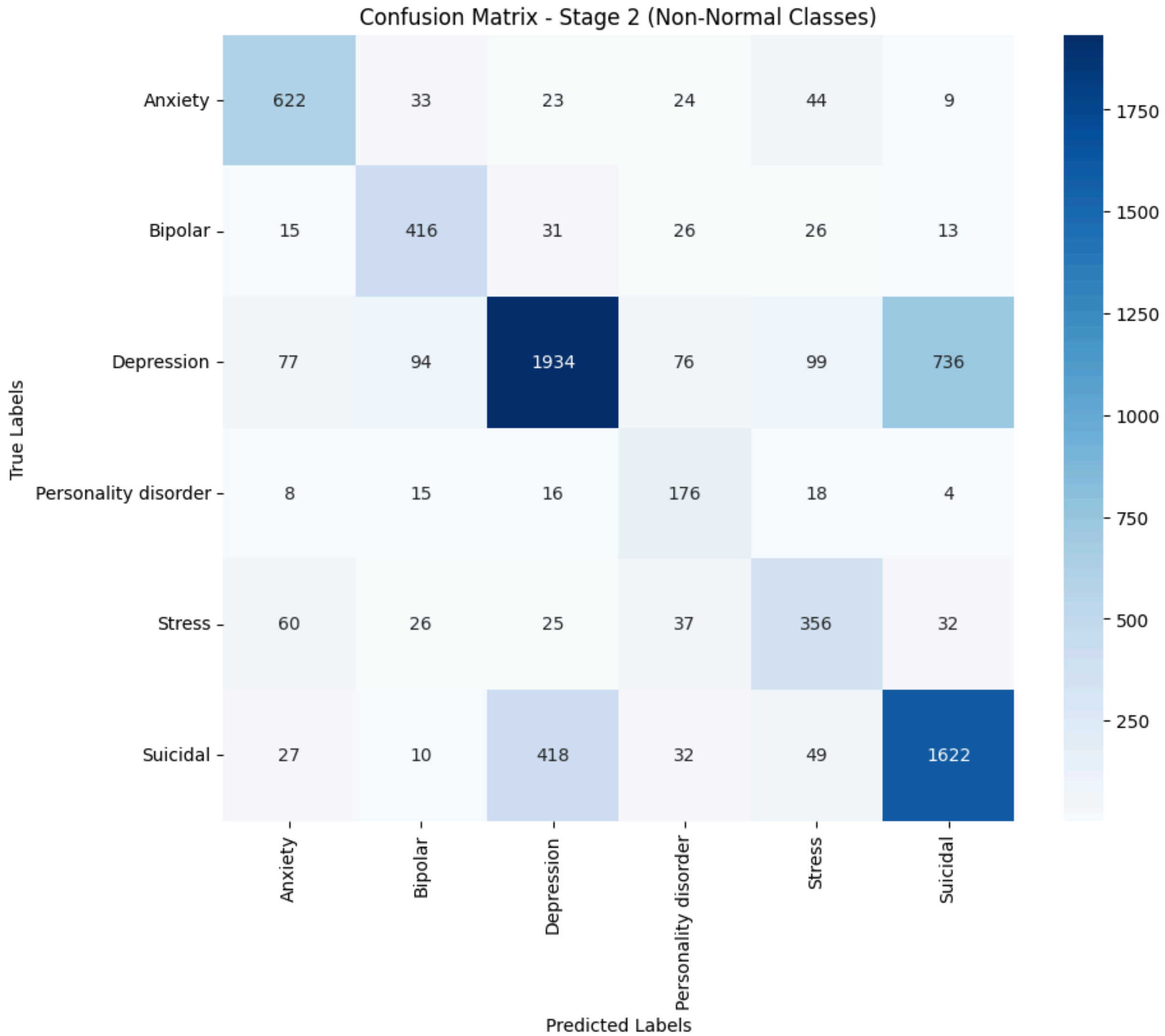
Classification Report

```
# Evaluate multi-class classifier
y_pred_stage2 = logistic_classifier.predict(X_test_tfidf_stage2)
print("Stage 2 (Multi-Class Classification) - Specific Conditions")
print("Accuracy:", accuracy_score(y_test_multi, y_pred_stage2))
print(classification_report(y_test_multi, y_pred_stage2))
conf_matrix_stage2= confusion_matrix(y_test_multi, y_pred_stage2)
print("Confusion Matrix:\n",conf_matrix_stage2)
```

```
Stage 2 (Multi-Class Classification) - Specific Conditions
Accuracy: 0.709088393968737
              precision    recall  f1-score   support

           0       0.77      0.82      0.80       755
           1       0.70      0.79      0.74       527
           2       0.79      0.64      0.71      3016
           3       0.47      0.74      0.58       237
           4       0.60      0.66      0.63       536
           5       0.67      0.75      0.71      2158

    accuracy                           0.71      7229
   macro avg       0.67      0.74      0.69      7229
weighted avg       0.72      0.71      0.71      7229

Confusion Matrix:
 [[ 622   33   23   24   44    9]
 [  15  416   31   26   26   13]
 [  77   94 1934   76   99  736]
 [   8   15   16  176   18    4]
 [  60   26   25   37  356   32]
 [  27   10  418   32   49 1622]]
```

Heat Map

```
# Plot heatmap for Stage 2
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix_stage2, annot=True, fmt="d", cmap="Blues", xticklabels=multi_encoder.classes_, yticklabels=multi_encoder.classes_)
plt.title("Confusion Matrix - Stage 2 (Non-Normal Classes)")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```



2.2 Neural Network Stage 2

Network Layers

```
# Define the layers in an array
layers = [
    Dense(units=120, activation='relu', input_shape=(X_train_tfidf_stage2.shape[1],),kernel_regularizer=l2(0.01)),  # Input Layer
    BatchNormalization(),
    Dropout(rate=0.3),  # Dropout Layer 1
    Dense(units=64, activation='relu',kernel_regularizer=l2(0.01)),  # Hidden Layer 1
    Dropout(rate=0.2),  # Dropout Layer 1
    Dense(units=16, activation='relu',kernel_regularizer=l2(0.01)),  # Hidden Layer 2

    Dense(units=6, activation='softmax')  # Output Layer
]

# Initialize the Sequential model
model = Sequential(layers)


# Compile the model: Using Adam optimizer, sparse categorical crossentropy loss, and accuracy as the metric
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Model Train

```
# Train the model on training data with validation on the test data
history = model.fit(X_train_tfidf_stage2.toarray(),
                    y_train_stage2,
                    epochs=20,
                    batch_size=256,
                    validation_split=0.3
                    )
```

```
Epoch 1/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 8s 29ms/step - accuracy: 0.6011 - loss: 3.0781 - val_accuracy: 0.2891 - val_loss: 2.1696
Epoch 2/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 6s 29ms/step - accuracy: 0.8278 - loss: 0.9390 - val_accuracy: 0.4247 - val_loss: 1.6755
Epoch 3/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - accuracy: 0.8322 - loss: 0.7690 - val_accuracy: 0.6268 - val_loss: 1.3151
Epoch 4/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 6s 29ms/step - accuracy: 0.8391 - loss: 0.7311 - val_accuracy: 0.6733 - val_loss: 1.2245
Epoch 5/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 9s 22ms/step - accuracy: 0.8442 - loss: 0.7100 - val_accuracy: 0.6598 - val_loss: 1.2445
Epoch 6/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 7s 33ms/step - accuracy: 0.8458 - loss: 0.7101 - val_accuracy: 0.6237 - val_loss: 1.3755
Epoch 7/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 24ms/step - accuracy: 0.8480 - loss: 0.6984 - val_accuracy: 0.6246 - val_loss: 1.3276
Epoch 8/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - accuracy: 0.8466 - loss: 0.7100 - val_accuracy: 0.6888 - val_loss: 1.2019
Epoch 9/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 7s 32ms/step - accuracy: 0.8500 - loss: 0.6941 - val_accuracy: 0.6455 - val_loss: 1.3591
Epoch 10/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - accuracy: 0.8501 - loss: 0.6930 - val_accuracy: 0.6942 - val_loss: 1.1857
Epoch 11/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - accuracy: 0.8501 - loss: 0.6890 - val_accuracy: 0.7055 - val_loss: 1.1137
Epoch 12/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 7s 33ms/step - accuracy: 0.8537 - loss: 0.6802 - val_accuracy: 0.6577 - val_loss: 1.3199
Epoch 13/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.8528 - loss: 0.6741 - val_accuracy: 0.6904 - val_loss: 1.2219
Epoch 14/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.8568 - loss: 0.6583 - val_accuracy: 0.6623 - val_loss: 1.3213
Epoch 15/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 7s 32ms/step - accuracy: 0.8545 - loss: 0.6643 - val_accuracy: 0.6919 - val_loss: 1.1865
Epoch 16/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 8s 22ms/step - accuracy: 0.8602 - loss: 0.6559 - val_accuracy: 0.6871 - val_loss: 1.2284
Epoch 17/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 7s 34ms/step - accuracy: 0.8563 - loss: 0.6606 - val_accuracy: 0.7103 - val_loss: 1.2132
Epoch 18/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - accuracy: 0.8584 - loss: 0.6563 - val_accuracy: 0.7073 - val_loss: 1.1678
Epoch 19/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - accuracy: 0.8601 - loss: 0.6460 - val_accuracy: 0.7015 - val_loss: 1.2234
Epoch 20/20
204/204 ━━━━━━━━━━━━━━━━━━━━ 7s 32ms/step - accuracy: 0.8627 - loss: 0.6461 - val_accuracy: 0.6916 - val_loss: 1.2593
```

```
nn_classifier = model
```

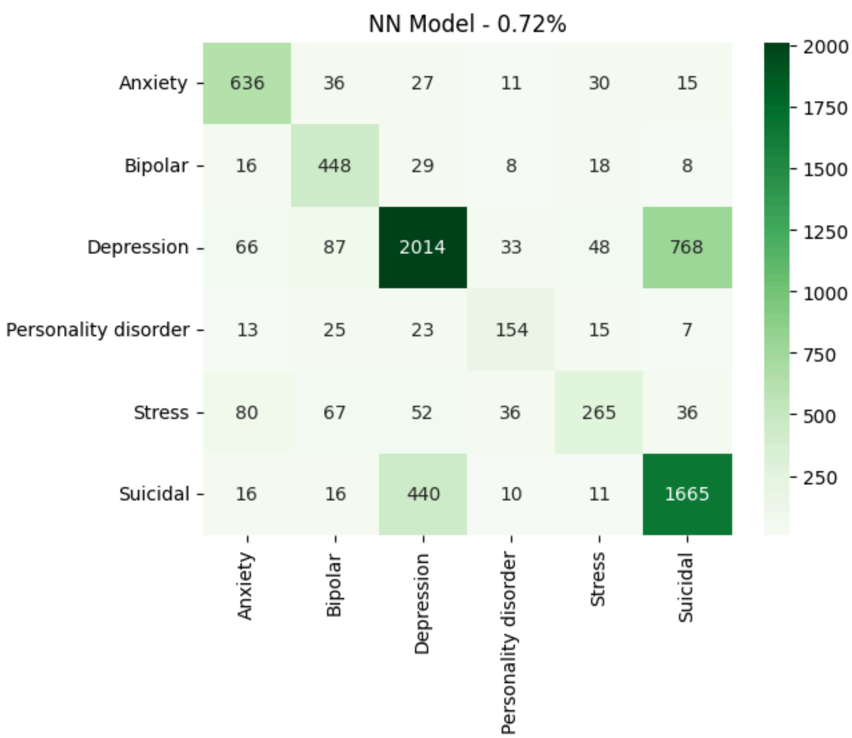
Classification Report

```
# Make predictions on the test set
y_pred_prob = model.predict(X_test_tfidf_stage2.toarray())
y_pred = y_pred_prob.argmax(axis=1)  # Convert probabilities to class predictions

# Calculate the accuracy
accuracy_score_final = accuracy_score(y_test_multi,y_pred)
print("\n")
print("Accuracy:", accuracy_nn)

# Compute the confusion matrix
classification_report_final =classification_report(y_test_multi, y_pred)
print(f"Overall Accuracy: {accuracy_score_final:.2f}")

print(classification_report_final)
conf_matrix_nn = confusion_matrix(y_test_multi,y_pred)

# Print classification report
print("Confusion Matrix:\n",conf_matrix_nn)
```

```
226/226 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

Accuracy: 0.7187716143311661
Overall Accuracy: 0.72
              precision    recall  f1-score   support

           0       0.77      0.84      0.80       755
           1       0.66      0.85      0.74       527
           2       0.78      0.67      0.72      3016
           3       0.61      0.65      0.63       237
           4       0.68      0.49      0.57       536
           5       0.67      0.77      0.72      2158

    accuracy                           0.72      7229
   macro avg       0.70      0.71      0.70      7229
weighted avg       0.72      0.72      0.71      7229

Confusion Matrix:
 [[ 636   36   27   11   30   15]
 [  16  448   29    8   18    8]
 [  66   87 2014   33   48  768]
 [  13   25   23  154   15    7]
 [  80   67   52   36  265   36]
 [  16   16  440   10   11 1665]]
```

Heat Map

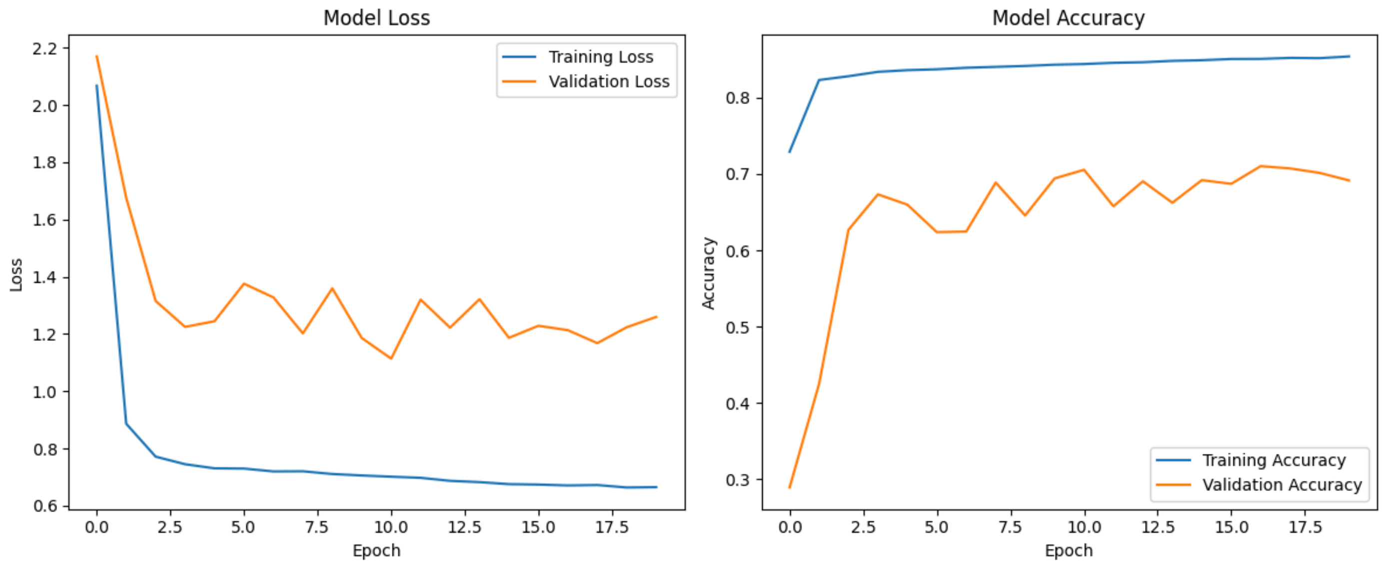
```
ax = sns.heatmap(conf_matrix_nn, annot = True, fmt='d', cmap='Greens', xticklabels=multi_encoder.classes_, yticklabels=multi_encoder.classes
ax.set_title(f'NN Model - {accuracy_nn:.2}%')
plt.show()
```



Model Loss and Accuracy

```
plt.figure(figsize=(12, 5))

# Plot training & validation loss values
plt.subplot(1, 2, 1)  # 1 row, 2 columns, 1st subplot
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
```

```
plt.legend(loc='upper right')

# Plot training & validation accuracy values
plt.subplot(1, 2, 2)  # 1 row, 2 columns, 2nd subplot
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

plt.tight_layout()  # Adjusts subplots to fit in the figure area.
plt.show()  # Display the plots
```



2.3 Best Model

choosing the best classfier for this stage

```
multi_classifier = logistic_classifier
```

combined Two Classifiers

3.1 Predict the test set

Initialize list for final predictions and true labels

[ ] ↳ *1 cell hidden*

Iterate Over the Test Samples

```
# Iterate through each sample in X_test
for i, test in enumerate(X_test):
    # Vectorize the text for Stage 1
    # vectorized_text_stage1 = vectorizer_stage1.transform([text])

    # Stage 1 Prediction (Binary Classification)
    stage1_prediction = binary_classifier.predict(test)[0]
```

```
    if stage1_prediction == binary_encoder.transform(['Normal'])[0]:  # If predicted as "Normal"
        final_predictions.append('Normal')
    else:
        # If predicted as "Non-Normal," vectorize for Stage 2 and predict specific condition
        # vectorized_text_stage2 = vectorizer_stage2.transform([text])
        stage2_prediction = multi_classifier.predict(test)[0]
        #stage2_prediction = model.predict(test).argmax(axis=1)

        final_predictions.append(multi_encoder.inverse_transform([stage2_prediction])[0])
```

3.2 Classification Report

```
accuracy_score_final=accuracy_score(ground_truth, final_predictions)
classification_report_final =classification_report(ground_truth, final_predictions)
# Final Combined Evaluation
print("\nCombined Two-Level Classification Results")
print(f"Overall Accuracy: {accuracy_score_final:.2f}")
print(classification_report_final)
```

```
Combined Two-Level Classification Results
Overall Accuracy: 0.76
                      precision    recall  f1-score   support

             Anxiety       0.75      0.80      0.77       755
             Bipolar       0.69      0.78      0.73       527
          Depression       0.78      0.64      0.70      3016
              Normal       0.91      0.91      0.91      3308
Personality disorder       0.46      0.72      0.56       237
              Stress       0.55      0.60      0.57       536
            Suicidal       0.66      0.73      0.69      2158

            accuracy                           0.76     10537
           macro avg       0.68      0.74      0.71     10537
        weighted avg       0.77      0.76      0.76     10537
```

3.3 Overall Heat Map