```
In [99]:
```

```
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import plotly.io as pio
pio.renderers.default="iframe"
import seaborn as sns
%matplotlib inline
import string
import re
import random
from imblearn.over_sampling import RandomOverSampler
from scipy.sparse import hstack # To combine sparse matrices
from wordcloud import WordCloud
from nltk.corpus import stopwords
from collections import Counter
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score, classification_report
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk import pos_tag
from collections import defaultdict
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier
from keras.models import Sequential
from keras.layers import Dense, LSTM, Embedding, Conv1D, GlobalMaxPooling
1D
import keras_tuner as kt
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
```

```
import tensorflow as tf

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
from scipy.sparse import hstack
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import LSTM, Dense, Embedding, Dropout, Inpu
t, Concatenate
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
import keras_tuner as kt

import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer

import warnings
warnings.filterwarnings("ignore")
```

Loading Data

```
In [100]: data=pd.read_csv('/kaggle/input/sentiment-analysis-for-mental-health/Comb
   ined Data.csv')
```

Preprocessing

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```
In [101]:
          data['status'].value_counts()
Out[101]:
          status
          Normal
                                    16351
          Depression
                                    15404
          Suicidal
                                    10653
          Anxiety
                                     3888
          Bipolar
                                     2877
          Stress
                                     2669
          Personality disorder
                                     1201
          Name: count, dtype: int64
In [102]:
          data.drop("Unnamed: 0",axis=1,inplace=True)
```

Detection and Removing Missing Values

```
In [103]:
          data.isnull().sum()
Out[103]:
                         362
           statement
           status
                           0
           dtype: int64
In [104]:
           data=data.dropna()
In [105]:
           data.isnull().sum()
Out[105]:
           statement
                         0
           status
           dtype: int64
```

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In [106]: data

Out[106]:

	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
3	I've shifted my focus to something else but I'	Anxiety
4	I'm restless and restless, it's been a month n	Anxiety
53038	Nobody takes me seriously I've (24M) dealt wit	 Anxiety
53038	Nobody takes me seriously I've (24M) dealt wit	Anxiety
53038 53039	Nobody takes me seriously I've (24M) dealt wit selfishness "I don't feel very good, it's lik	Anxiety

52681 rows × 2 columns

In []:

EDA

In [107]: data.describe()

Out[107]:

	statement	status
count	52681	52681
unique	51073	7
top	what do you mean?	Normal
freq	22	16343

```
In [108]:
    status=data['status'].value_counts().unique()
    status

Out[108]:
    array([16343, 15404, 10652, 3841, 2777, 2587, 1077])
```

```
In [109]:
          labels=['Anxiety','Normal','Depression','Suicidal','Stress','Bipolar','Pe
          rsonality Disorder']
          colors=['Gold','mediumturquoise','darkorange','lightgreen','saddlebrow
          n','rebeccapurple']
          fig = go.Figure(
              data=[
                  go.Pie(
                      labels=labels,
                      values=status,
                      textinfo='label+percent',
                      textfont=dict(
                          size=15,
                          color='black'
                      ),
                      marker=dict(colors=colors, pattern=dict(shape=[".", "x", "+",
          "-",'|','+','x']))
          fig.show()
```

Out[110]:

	statement	status	num_of_words	num_of_sentence	num_of_characters
0	oh my gosh	Anxiety	3	1	10
1	trouble sleeping, confused mind, restless hear	Anxiety	10	2	64
2	All wrong, back off dear, forward doubt. Stay	Anxiety	14	2	78
3	I've shifted my focus to something else but I'	Anxiety	11	1	61
4	I'm restless and restless, it's been a month n	Anxiety	14	2	72
53038	Nobody takes me seriously I've (24M) dealt wit	Anxiety	322	16	1766
53039	selfishness "I don't feel very good, it's lik	Anxiety	198	12	1012
53040	Is there any way to sleep better? I can't slee	Anxiety	17	2	85
53041	Public speaking tips? Hi, all. I have to give	Anxiety	74	6	401
53042	I have really bad door anxiety! It's not about	Anxiety	79	3	417

52681 rows × 5 columns

Status: Anxiety

Statement: finger nails... beaus lines So recently within the past few months i have started to develop horizontal ridges on my finger and to e nails. I googled and discovered they are called beaus lines and they often indicate different diseases. I'm in pretty good health and eat w ell and exercise often but I'm still concerned as to why i have these horizontal ridges on my nails?? please help if you have any insight

Status: Bipolar

Statement: Realizations In a very bad depression now. And I don't know if it's the depression or what, but I'm am realizing most of my family and friends treat me like shit and really take me for granted. My husb and, my kids, hell even my mom. Starting to realize my support system isn't that great. That only makes my depression worse!

Status: Depression

Statement: Every day around my family I am innable to show any emotio n. In home it is like "hot and cold" they can yell at me and tell me h ow useless I am and then because I guess they feel guilty they either apologise or try changing the subject . I have only one friend which I really REALLY care for but their life is much more complicated and I f eel like shit ...I cannot help I can"t do amything they want to commit s. and I am unable to stop that . I know nothing ,I do nothing , I have nothing... the only thing I feel is confusion ,emptyness or irritati on I do not know what is happening to me anymore

Status: Normal

Statement: Watching: KAWAJI ZONE+

Status: Personality disorder

Statement: My first therapy appointment in a long time I have had bad luck with therapists in the past but decided to try again. I am mainly going to overcome a fear of driving. I have driven before back as a te enager and the process was going well but there were some things that happened that then hindered it. Before in therapy, I didn't have specific goals and I don't think that helped.

Status: Stress

Statement: I'm scared I'm going to slip the next time I get in the car or on my motorcycle and just plow into something at full speed just be cause it'd be so easy and it might end all the pain. But then I don't want to do that, because I have a safe car, and I wear full safety gea r when I ride, so those are both maybes. I don't have a gun. I find my thoughts straying from just using one if I had one to thinking of plac es I could buy one from. Does Walmart sell them in California?

Status: Suicidal

Statement: My life has gotten worse for 10 years. Nothing has worked to make it better. I just cannot do this anymore, I am tired..I am just so fucking tired of every day trying to cope with everything. I have not lived in so long. My mental health and chronic pain have completely engulfed my life. I am a she will of who I once was. I am a burden to my family and girlfriend. I do not even know if she loves me anymore but I cannot blame her. I have lost myself. I have lost her. I have nob ody. I cannot FUCKING DO THIS

```
In [112]:
    avg_word=data.groupby('status')['num_of_words'].mean().reset_index()
    avg_word
```

Out[112]:

	status	num_of_words
0	Anxiety	143.837022
1	Bipolar	176.200216
2	Depression	168.021488
3	Normal	17.246283
4	Personality disorder	179.346332
5	Stress	114.585234
6	Suicidal	146.440293

```
In [113]:
    avg_sent=data.groupby('status')['num_of_sentence'].mean().reset_index()
    avg_sent
```

Out[113]:

	status	num_of_sentence
0	Anxiety	8.490758
1	Bipolar	11.046093
2	Depression	7.830369
3	Normal	1.522793
4	Personality disorder	10.675023
5	Stress	6.474681
6	Suicidal	8.794217

Out[114]:

	status	num_of_characters
0	Anxiety	764.681073
1	Bipolar	946.074901
2	Depression	844.031161
3	Normal	90.244447
4	Personality disorder	956.731662
5	Stress	613.545419
6	Suicidal	734.967330

```
In [115]: col=['num_of_words','num_of_sentence','num_of_characters']
```

```
In [116]:    melted_data=data[col].melt(var_name='Variable', value_name='Value')
```

In [117]:
 fig= px.box(melted_data,y='Variable',x='Value', title='Distribution of Nu
 m of Statements',color='Variable')
 fig.update_layout(xaxis_title='Variables',yaxis_title='Values', showlegen
 d=True)
 fig.layout.legend.x=1
 fig.layout.legend.y=1
 fig.layout.legend.xref='paper'
 fig.layout.legend.yref='paper'
 fig.layout.legend.font.size=12
 fig.layout.legend.title = 'Column Names'
 fig.layout.legend.bordercolor = 'indigo'
 fig.layout.legend.bordercolor = 'indigo'
 fig.layout.legend.borderwidth = 4

fig.show()

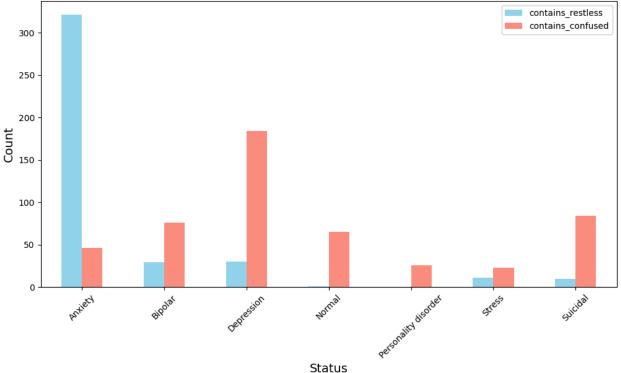
```
In [118]:
          fig = go.Figure()
          fig.add_trace(go.Scatter(
              x=avg_word['status'],
              y=avg_word['num_of_words'],
              mode='lines+markers',
              name='Words',
          ))
          fig.add_trace(go.Scatter(
              x=avg_sent['status'],
              y=avg_sent['num_of_sentence'],
              mode='lines+markers',
              name='Sentence',
          ))
          fig.add_trace(go.Scatter(
              x=avg_char['status'],
              y=avg_char['num_of_characters'],
              mode='lines+markers',
              name='Characters',
          ))
          fig.update_layout(
              title='Mean of Number of Words, Sentences, and Characters',
              xaxis_title='Status',
              yaxis_title='Mean Count',
              xaxis=dict(tickmode='linear', tick0=0, dtick=1),
              legend=dict(title='Column Name'),
              hovermode='x'
          fig.show()
```

```
In [119]:
```

```
data['contains_restless'] = data['statement'].dropna().apply(lambda x: 'r
estless' in x.lower())
data['contains_confused'] = data['statement'].dropna().apply(lambda x: 'c
onfused' in x.lower())

word_counts = data.groupby('status')[['contains_restless', 'contains_conf
used']].sum()
word_counts.plot(kind='bar', figsize=(12, 6), color=['skyblue', 'salmo
n'], alpha=0.9)
plt.title("Frequency of 'Restless' and 'Confused' by Mental Health Statu
s", fontsize=16)
plt.xlabel("Status", fontsize=14)
plt.ylabel("Count", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```





Lower Casing

```
In [120]: data['statement']=data['statement'].str.lower()
    data
```

Out[120]:

	statement	status	num_of_words	num_of_sentence	num_of_characters	contains_restless
0	oh my gosh	Anxiety	3	1	10	False
1	trouble sleeping, confused mind, restless hear	Anxiety	10	2	64	True
2	all wrong, back off dear, forward doubt. stay 	Anxiety	14	2	78	True
3	i've shifted my focus to something else but i'	Anxiety	11	1	61	False
4	i'm restless and restless, it's been a month n	Anxiety	14	2	72	True
53038	nobody takes me seriously i've (24m) dealt wit	Anxiety	322	16	1766	False
53039	selfishness "i don't feel very good, it's lik	Anxiety	198	12	1012	False
53040	is there any way to sleep better? i can't slee	Anxiety	17	2	85	False
53041	public speaking tips? hi, all. i have to give	Anxiety	74	6	401	False
53042	i have really bad door anxiety! it's not about	Anxiety	79	3	417	False
4						

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Removing Punctuation, Unicode Characters, Unwanted Patterns and URL

```
In [121]:
          def removing(text):
              #for removing URLs
              text=re.sub(r'http[s]?://\S+', '', text)
              text = re.sub(r'https?://\S+|www\.\S+', '', text)
              #removing markdown-style links
              text=re.sub(r'\[.*?\]\(.*?\)','',text)
              #removing square brackets
              text = re.sub(r'\setminus[.*?\setminus]', '', text)
              #remove HTML tags
              text = re.sub(r'<.*?>+', '', text)
              #remove@
              text=re.sub(r'@\w+','',text)
              #remove punctuation and special characters
              text=re.sub(r'[^\w\s]','',text)
              text = re.sub(r'[%s]' % re.escape(string.punctuation), '', text)
              #removing age and gender patterns like 24M or 30F
              text=re.sub(r'\b\d{1,3}[mf]\b','',text)
              text=re.sub(r'\b\d{1,3}[MF]\b','',text)
              pattern = r'\b(?:ive|im|hes|shes|theyre|weve|youve|cant|wont|isnt|are
          nt|wasnt|hi|werent|havent|hasnt|didnt|doesnt|youre|id|hed|dont|else|shed|
          theyd|itd|wed|youd)\b'
              # Remove the matching contractions (case-insensitive)
              text = re.sub(pattern, '', text, flags=re.IGNORECASE)
              #removing new lines
              text = re.sub(r'\n', '', text)
              return text.strip()
          data['statement']=data['statement'].apply(removing)
          data.statement
```

Out[121]:

0	oh my gosh
1	trouble sleeping confused mind restless heart
2	all wrong back off dear forward doubt stay in
3	shifted my focus to something but still worried
4	restless and restless its been a month now boy
53038	nobody takes me seriously dealt with depress
53039	selfishness i feel very good its like i bel
53040	is there any way to sleep better i sleep most
53041	public speaking tips all i have to give a pre
53042	i have really bad door anxiety its not about b
Name:	statement, Length: 52681, dtype: object

```
In [122]:
    stop_words=set(stopwords.words('english'))
    def remove_stopwords(text):
        tokens = word_tokenize(text)
        tokens = [word for word in tokens if word not in stop_words]
        return ' '.join(tokens)

    data['cleaned_statement'] = data['statement'].apply(lambda x: remove_stop words(x))
        data
```

Out[122]:

	statement	status	num_of_words	num_of_sentence	num_of_characters	contains_restless
0	oh my gosh	Anxiety	3	1	10	False
1	trouble sleeping confused mind restless heart	Anxiety	10	2	64	True
2	all wrong back off dear forward doubt stay in	Anxiety	14	2	78	True
3	shifted my focus to something but still worried	Anxiety	11	1	61	False
4	restless and restless its been a month now boy	Anxiety	14	2	72	True
53038	nobody takes me seriously dealt with depress	Anxiety	322	16	1766	False
53039	selfishness i feel very good its like i bel	Anxiety	198	12	1012	False
53040	is there any way to sleep better i sleep most	Anxiety	17	2	85	False
53041	public speaking tips all i have to give a pre	Anxiety	74	6	401	False
53042	i have really bad door anxiety its not about b	Anxiety	79	3	417	False

```
In [123]:
    data['tokens']=data['cleaned_statement'].apply(word_tokenize)
    data
```

Out[123]:

oh my gosh	Anxiety	3	1	10	False
trouble sleeping confused mind restless heart	Anxiety	10	2	64	True
all wrong back off dear forward doubt stay in	Anxiety	14	2	78	True
shifted my focus to something but still worried	Anxiety	11	1	61	False
restless and restless its been a month now boy	Anxiety	14	2	72	True
nobody takes me seriously dealt with depress	Anxiety	322	16	1766	False
selfishness i feel very good its like i bel	Anxiety	198	12	1012	False
is there any way to sleep better i sleep most	Anxiety	17	2	85	False
public speaking tips all i have to give a pre	Anxiety	74	6	401	False
i have really bad door anxiety its not about b	Anxiety	79	3	417	False
	gosh trouble sleeping confused mind restless heart all wrong back off dear forward doubt stay in shifted my focus to something but still worried restless and restless its been a month now boy nobody takes me seriously dealt with depress selfishness i feel very good its like i bel is there any way to sleep better i sleep most public speaking tips all i have to give a pre i have really bad door anxiety its not about	trouble sleeping confused mind restless heart all wrong back off dear forward doubt stay in shifted my focus to something but still worried restless and restless its been a month now boy nobody takes me seriously dealt with depress selfishness i feel very good its like i bel is there any way to sleep better i sleep most public speaking tips all i have to give a pre i have really bad door anxiety its not about Anxiety Anxiety Anxiety Anxiety Anxiety Anxiety	trouble sleeping confused mind restless heart all wrong back off dear forward doubt stay in shifted my focus to something but still worried restless and restless its been a month now boy nobody takes me seriously dealt with depress selfishness i feel very good its like i bel is there any way to sleep better i sleep most public speaking tips all i have really bad door anxiety its not about	trouble sleeping confused mind restless heart all wrong back off dear forward doubt stay in shifted my focus to something but still worried restless and restless its been a month now boy nobody takes me seriously dealt with depress selfishness i feel very good its like i bel is there any way to sleep better i sleep most public speaking tips all i have to give a pre i have really bad door anxiety its not about	gosh Anxiety of trouble sleeping confused mind restless heart all wrong back off dear forward doubt stay in shifted my focus to something but still worried restless and restless its been a month now boy nobody takes me seriously dealt with depress selfishness i feel word is feel word. Anxiety and anxiety are any way to sleep better i sleep better i sleep better i speaking tips all i have to give a pre i have really bad door anxiety is not about the feel with the process Anxiety and the feel way and th

POS Analysis

```
In [124]:
          def pos_analysis(tokens):
              pos_mapping = {
                  'JJ': 'Adjective', 'JJR': 'Adjective', 'JJS': 'Adjective',
                  'NN': 'Noun', 'NNS': 'Noun', 'NNP': 'Noun', 'NNPS': 'Noun',
                  'VB': 'Verb', 'VBD': 'Verb', 'VBG': 'Verb', 'VBN': 'Verb', 'VBP':
          'Verb', 'VBZ': 'Verb',
                  'RB': 'Adverb', 'RBR': 'Adverb', 'RBS': 'Adverb',
              }
              tagged = pos_tag(tokens)
              pos_count = defaultdict(int)
              pos_words = defaultdict(list)
              for word, tag in tagged:
                  if tag in pos_mapping:
                      category = pos_mapping[tag]
                      pos_count[category] += 1
                      pos_words[category].append(word)
              return {
                  'pos_count': pos_count,
                  'pos_words': pos_words,
              }
```

```
In [125]:
          def analyze_row(row):
              result = pos_analysis(row)
              return pd.Series({
                  'Adjectives': ', '.join(result['pos_words'].get('Adjective',
          [])),
                  'Adjective_Count': result['pos_count'].get('Adjective', 0),
                  'Nouns': ', '.join(result['pos_words'].get('Noun', [])),
                  'Noun_Count': result['pos_count'].get('Noun', 0),
                  'Verbs': ', '.join(result['pos_words'].get('Verb', [])),
                  'Verb_Count': result['pos_count'].get('Verb', 0),
                  'Adverbs': ', '.join(result['pos_words'].get('Adverb', [])),
                  'Adverb_Count': result['pos_count'].get('Adverb', 0),
              })
          pos_results = data['tokens'].apply(analyze_row)
          data = pd.concat([data, pos_results], axis=1)
```

```
In [126]:
    pd.set_option('display.max_columns', None)
    data.head()
```

Out[126]:

	statement	status	num_of_words	num_of_sentence	num_of_characters	contains_restless	conta
0	oh my gosh	Anxiety	3	1	10	False	False
1	trouble sleeping confused mind restless heart	Anxiety	10	2	64	True	True
2	all wrong back off dear forward doubt stay in	Anxiety	14	2	78	True	False
3	shifted my focus to something but still worried	Anxiety	11	1	61	False	Fals€
4	restless and restless its been a month now boy	Anxiety	14	2	72	True	False
4							•

```
In [127]:
    numeric_cols = data.select_dtypes(include=['int', 'float']).columns
    for col in numeric_cols:
        print(col, (data[col] == 0).sum())
```

```
num_of_words 0
num_of_sentence 0
num_of_characters 0
Adjective_Count 7900
Noun_Count 1053
Verb_Count 6146
Adverb_Count 14463
```

```
In [128]:
    pos_cols = [
        'Adjective_Count',
        'Noun_Count',
        'Verb_Count',
        'Adverb_Count'
]
```

```
In [129]:
    data_avg = data.groupby('status')[pos_cols + ['num_of_words']].mean().res
    et_index()
```

```
for col in pos_cols:
    ratio_col = col + '_ratio'
    data_avg[ratio_col] = data_avg[col] / data_avg['num_of_words']
```

```
In [131]: data_avg
```

Out[131]:

	status	Adjective_Count	Noun_Count	Verb_Count	Adverb_Count	num_of_words	Adjective_
0	Anxiety	12.360844	27.221297	16.610518	6.813330	143.837022	0.085936
1	Bipolar	15.395031	31.979834	20.339215	8.074181	176.200216	0.087372
2	Depression	13.160997	28.320696	18.935666	7.857310	168.021488	0.078329
3	Normal	1.441106	4.111913	1.871015	0.700973	17.246283	0.083560
4	Personality disorder	14.773445	30.737233	20.568245	8.984215	179.346332	0.082374
5	Stress	9.185543	21.439505	13.271357	5.020487	114.585234	0.080163
6	Suicidal	11.149268	23.557360	16.938415	6.752816	146.440293	0.076135
4							•

```
In [132]:
    pos_ratio_cols = [col + '_ratio' for col in pos_cols]

    melted_counts = data_avg.melt(
        id_vars='status',
        value_vars=pos_cols,
        var_name='pos_type',
        value_name='average_count'
)

    melted_ratios = data_avg.melt(
        id_vars='status',
        value_vars=pos_ratio_cols,
        var_name='pos_type',
        value_name='ratio'
)
```

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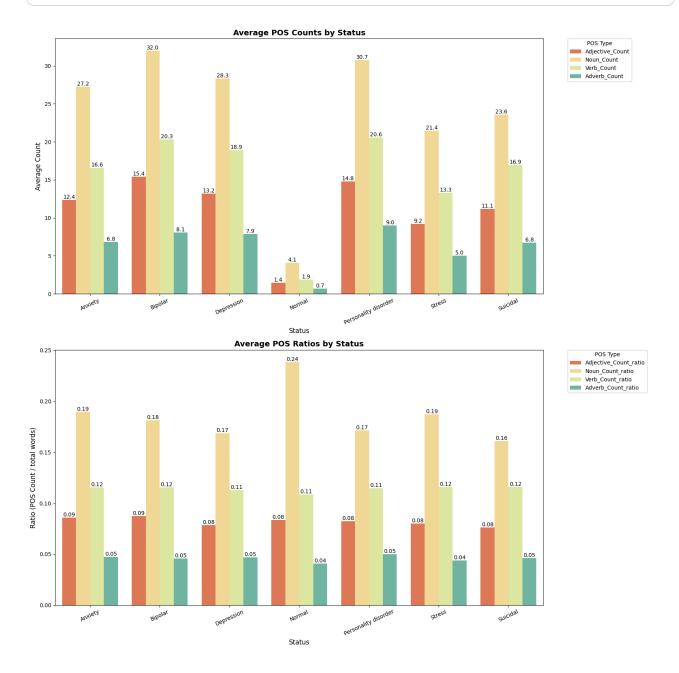
```
In [133]:
          fig, axes = plt.subplots(2, 1, figsize=(16, 16))
          palette = sns.color_palette("Spectral", n_colors=len(pos_cols))
          sns.barplot(
              data=melted_counts,
              x='status',
              y='average_count',
              hue='pos_type',
              ax=axes[0],
              palette=palette
          axes[0].set_title('Average POS Counts by Status', fontsize=14, fontweight
          ='bold')
          axes[0].set_xlabel('Status', fontsize=12)
          axes[0].set_ylabel('Average Count', fontsize=12)
          axes[0].tick_params(axis='x', rotation=25)
          for container in axes[0].containers:
              axes[0].bar_label(container, fmt="%.1f", label_type="edge", fontsize=
          10)
          axes[0].legend(title='POS Type', bbox_to_anchor=(1.05, 1), loc='upper lef
          t', borderaxespad=0)
          sns.barplot(
              data=melted_ratios,
              x='status',
              y='ratio',
              hue='pos_type',
              ax=axes[1],
              palette=palette
          axes[1].set_title('Average POS Ratios by Status', fontsize=14, fontweight
          ='bold')
          axes[1].set_xlabel('Status', fontsize=12)
          axes[1].set_ylabel('Ratio (POS Count / total words)', fontsize=12)
          axes[1].tick_params(axis='x', rotation=25)
          for container in axes[1].containers:
```

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```
axes[1].bar_label(container, fmt="%.2f", label_type="edge", fontsize=
10)

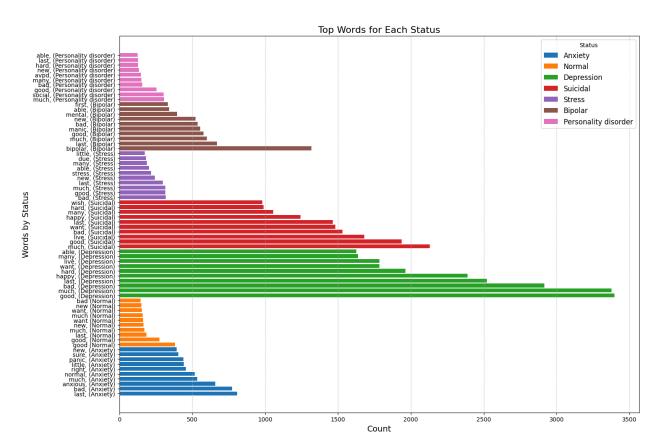
axes[1].legend(title='POS Type', bbox_to_anchor=(1.05, 1), loc='upper lef
t', borderaxespad=0)

plt.tight_layout()
plt.show()
```



plt.show()

```
In [134]:
         plot_data = []
          statuses = data['status'].dropna().unique()
          for status in statuses:
              words = ' '.join(data[data['status'] == status]['Adjectives'].dropna
          ()).split()
              word_counts = Counter(words).most_common(10)
              for word, count in word_counts:
                  plot_data.append({'status': status, 'word': word, 'count': coun
          t } )
         word_df = pd.DataFrame(plot_data)
          plt.figure(figsize=(15, 10))
          statuses = word_df['status'].unique()
         for i, status in enumerate(statuses):
              subset = word_df[word_df['status'] == status]
              plt.barh(subset['word'] + f" ({status})", subset['count'], label=stat
          us)
         plt.title("Top Words for Each Status", fontsize=16)
          plt.xlabel("Count", fontsize=14)
          plt.ylabel("Words by Status", fontsize=14)
          plt.legend(title="Status", loc='upper right', fontsize=12)
          plt.tight_layout()
          plt.grid(axis='x', linestyle='--', alpha=0.7)
```



```
In [ ]:
        import math
        num_cols = 2
        num_rows = math.ceil(len(statuses) / num_cols)
        plt.figure(figsize=(14, 4 * num_rows))
        for i, status in enumerate(statuses):
            df_sub = data.loc[data['status'] == status, 'cleaned_statement'].drop
        na()
            text_all = " ".join(df_sub.tolist())
            vectorizer = CountVectorizer(ngram_range=(2,2), max_features=50)
            X = vectorizer.fit_transform([text_all])
            bigram_freqs = X.toarray()[0]
            bigram_features = vectorizer.get_feature_names_out()
            freq_dict = dict(zip(bigram_features, bigram_freqs))
            if sum(freq_dict.values()) == 0:
                print(f"No bigrams found for status '{status}'. Skipping.")
                continue
            wordcloud = WordCloud(
                width=800,
                height=400,
                background_color='white',
                colormap='plasma'
            ).generate_from_frequencies(freq_dict)
            ax = plt.subplot(num_rows, num_cols, i + 1)
            ax.imshow(wordcloud, interpolation='bilinear')
            ax.set_title(f"Bigrams WordCloud: {status}", fontsize=14, pad=10)
            ax.axis("off")
        plt.tight_layout()
        plt.show()
```

data

Out[136]:

	statement	status	num_of_words	num_of_sentence	num_of_characters	contains_restless
0	oh my gosh	Anxiety	3	1	10	False
1	trouble sleeping confused mind restless heart	Anxiety	10	2	64	True
2	all wrong back off dear forward doubt stay in	Anxiety	14	2	78	True
3	shifted my focus to something but still worried	Anxiety	11	1	61	False
4	restless and restless its been a month now boy	Anxiety	14	2	72	True
53038	nobody takes me seriously dealt with depress	Anxiety	322	16	1766	False
53039	selfishness i feel very good its like i bel	Anxiety	198	12	1012	False
53040	is there any way to sleep better i sleep most	Anxiety	17	2	85	False
53041	public speaking tips all i have to give a pre	Anxiety	74	6	401	False

	statement	status	num_of_words	num_of_sentence	num_of_characters	contains_restless
53042	i have really bad door anxiety its not about b	Anxiety	79	3	417	False

52681 rows × 17 columns

After Label Encoding to Status

- Anxiety -> 0
- Bipolar -> 1
- Depression -> 2
- Normal -> 3
- Personal Disorder -> 4
- Stress -> 5
- Suicidal -> 6

We need to make label encoding Adjectives, Nouns, Verbs, Adverbs colums to find which of them used for detecting to status.

```
In [141]:
    data['Adj_le'] = le.fit_transform(data['Adjectives'])
    data['N_le'] = le.fit_transform(data['Nouns'])
    data['V_le'] = le.fit_transform(data['Verbs'])
    data['Adv_le'] = le.fit_transform(data['Adverbs'])
```

```
In [143]: data_copy
```

Out[143]:

	status	num_of_words	num_of_sentence	num_of_characters	cleaned_statement	Adjective_0
0	Anxiety	3	1	10	oh gosh	0
1	Anxiety	10	2	64	trouble sleeping confused mind restless heart	1
2	Anxiety	14	2	78	wrong back dear forward doubt stay restless re	3
3	Anxiety	11	1	61	shifted focus something still worried	0
4	Anxiety	14	2	72	restless restless month boy mean	2
53038	Anxiety	322	16	1766	nobody takes seriously dealt depressionanxiety	30
53039	Anxiety	198	12	1012	selfishness feel good like belong world think	19
53040	Anxiety	17	2	85	way sleep better sleep nights meds help	2
53041	Anxiety	74	6	401	public speaking tips give presentation work ne	8
53042	Anxiety	79	3	417	really bad door anxiety scared lock door somet	9
4						•

52681 rows × 13 columns

```
In [144]:
    feature_cols = [
        'Adjective_Count', 'Noun_Count', 'Verb_Count', 'Adverb_Count',
        'num_of_words', 'num_of_sentence', 'num_of_characters'
    ]

X_fe = data[feature_cols]
    y_fe = data['status_label']
```

```
In [145]:
    rf = RandomForestClassifier(n_estimators=100, random_state=42)
    rf.fit(X_fe, y_fe)

importances = rf.feature_importances_

data_importances = pd.DataFrame({
        'feature': feature_cols,
        'importance': importances
}).sort_values('importance', ascending=False)

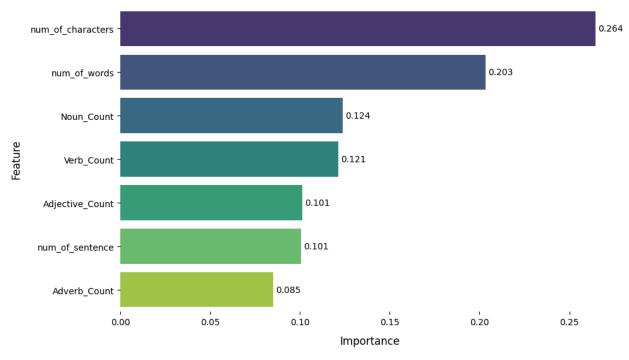
data_importances
```

Out[145]:

	feature	importance
6	num_of_characters	0.264471
4	num_of_words	0.203271
1	Noun_Count	0.123722
2	Verb_Count	0.121228
0	Adjective_Count	0.101448
5	num_of_sentence	0.100645
3	Adverb_Count	0.085215

```
In [146]:
          plt.figure(figsize=(10, 6))
          g = sns.barplot(
              data=data_importances,
              x='importance',
              y='feature',
              palette='viridis'
          )
          plt.title('Feature Importance (Random Forest)', fontsize=14, fontweight
          ='bold', pad=12)
          plt.xlabel('Importance', fontsize=12, labelpad=10)
          plt.ylabel('Feature', fontsize=12, labelpad=10)
          for container in g.containers:
              g.bar_label(container, fmt='%.3f', label_type='edge', padding=3)
          sns.despine(left=True, bottom=True)
          plt.tight_layout()
          plt.show()
```

Feature Importance (Random Forest)



Feature Selection & Spilitting Data as Test and Train

```
In [147]:
    df=data[['status','cleaned_statement','num_of_characters','num_of_word
    s']]
```

```
In [148]: df.isnull().sum()
```

Out[148]:

status 0
cleaned_statement 0
num_of_characters 0
num_of_words 0
dtype: int64

```
In [149]: df
```

Out[149]:

	status	cleaned_statement	num_of_characters	num_of_words
0	Anxiety	oh gosh	10	3
1	Anxiety	trouble sleeping confused mind restless heart	64	10
2	Anxiety	wrong back dear forward doubt stay restless re	78	14
3	Anxiety	shifted focus something still worried	61	11
4	Anxiety	restless restless month boy mean	72	14
53038	Anxiety	nobody takes seriously dealt depressionanxiety	1766	322
53039	Anxiety	selfishness feel good like belong world think	1012	198
53040	Anxiety	way sleep better sleep nights meds help	85	17
53041	Anxiety	public speaking tips give presentation work ne	401	74
53042	Anxiety	really bad door anxiety scared lock door somet	417	79

52681 rows × 4 columns

Model Selection

Logistic Regression Naive Bayes SVM Random Forest XGBoost LightGBM CatBoost LSTM BERT GPT CNN + Global Pooling Pretrained Embedding + CNN

Perform hyperparameter tuning with tools like KerasTuner or GridSearchCV.

Logistic Regression

```
In [156]:
          lr=LogisticRegression(random_state=42, max_iter=5000)
          lr_params={'penalty': ['11', '12', 'elasticnet'], 'C':[0.01, 0.1, 1, 10, 10]
          0]}
          lr_grid=GridSearchCV(lr, lr_params, cv=3, scoring='accuracy')
          lr_grid.fit(X_train,y_train_le)
          print("Best Logistic Regression Params:", lr_grid.best_params_)
          Best Logistic Regression Params: {'C': 1, 'penalty': '12'}
In [157]:
          best_lr_model=lr_grid.best_estimator_
In [158]:
          best_lr_model
Out[158]:
                             LogisticRegression
         LogisticRegression(C=1, max_iter=5000, random_state=42)
In [159]:
          y_pred_lr=best_lr_model.predict(X_test)
In [160]:
          accuracy_lr=accuracy_score(y_test_le,y_pred_lr)
In [161]:
          print(f"Accuracy of the best Logistic Regression model: {accuracy_lr * 10
          0:.2f}%")
```

Accuracy of the best Logistic Regression model: 74.83%

```
In [162]:
```

```
print("Classification Report for Logistic Regression:")
print(classification_report(y_test_le, y_pred_lr))
```

Classification Report for Logistic Regression:

	precision	recall	f1-score	support
0	0.82	0.71	0.76	768
1	0.89	0.62	0.73	556
2	0.68	0.74	0.71	3081
3	0.83	0.95	0.88	3269
4	0.89	0.40	0.55	215
5	0.68	0.37	0.47	517
6	0.67	0.62	0.64	2131
accuracy			0.75	10537
macro avg	0.78	0.63	0.68	10537
weighted avg	0.75	0.75	0.74	10537

FNN

X_text=df['cleaned_statement']

y=df['status']

X train, X test, y train, y test

y_train_le=le.fit_transform(y_train) y_test_le=le.fit_transform(y_test)

```
In [163]:
          from tensorflow.keras.optimizers import Adam
          nn_model = Sequential([
              Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
              Dropout(0.3),
              Dense(64, activation='relu'),
              Dropout(0.3),
              Dense(len(le.classes_), activation='softmax')
          ])
          optimizer = Adam(learning_rate=0.0005)
          # Compile the model with the optimizer
          nn_model.compile(optimizer=optimizer,
                           loss='sparse_categorical_crossentropy',
                           metrics=['accuracy'])
          nn_history = nn_model.fit(
              X_train.toarray(),
              y_train_le,
              epochs=10,
              batch_size=64,
              validation_split=0.2,
              verbose=1
          )
          test_loss, test_accuracy = nn_model.evaluate(X_test.toarray(), y_test_le,
          verbose=0)
          print(f"Test Accuracy: {test_accuracy:.4f}")
          from sklearn.metrics import classification_report
          y_pred_fnn = nn_model.predict(X_test.toarray(), verbose=0).argmax(axis=1)
          print(classification_report(y_test_le, y_pred_fnn, target_names=le.classe
          s_))
```

```
Epoch 1/10
- accuracy: 0.5753 - val_loss: 0.7784 - val_accuracy: 0.7192
Epoch 2/10
- accuracy: 0.7435 - val_loss: 0.6849 - val_accuracy: 0.7494
Epoch 3/10
- accuracy: 0.7941 - val_loss: 0.6642 - val_accuracy: 0.7561
Epoch 4/10
- accuracy: 0.8223 - val_loss: 0.6694 - val_accuracy: 0.7580
Epoch 5/10
- accuracy: 0.8475 - val_loss: 0.6952 - val_accuracy: 0.7529
Epoch 6/10
- accuracy: 0.8682 - val_loss: 0.7228 - val_accuracy: 0.7498
Epoch 7/10
- accuracy: 0.8852 - val_loss: 0.7522 - val_accuracy: 0.7480
Epoch 8/10
- accuracy: 0.9029 - val_loss: 0.8014 - val_accuracy: 0.7461
Epoch 9/10
- accuracy: 0.9204 - val_loss: 0.8464 - val_accuracy: 0.7461
Epoch 10/10
- accuracy: 0.9298 - val_loss: 0.8812 - val_accuracy: 0.7447
Test Accuracy: 0.7368
             precision recall f1-score
                               support
                           0.76
                     0.74
                                  768
       Anxiety
               0.79
       Bipolar
               0.81
                     0.70
                           0.75
                                  556
     Depression
               0.66
                     0.70
                           0.68
                                 3081
        Normal
               0.88
                     0.91
                           0.89
                                 3269
Personality disorder
               0.76
                     0.54
                           0.63
                                 215
        Stress
               0.58
                     0.49
                           0.53
                                  517
       Suicidal
               0.62
                     0.62
                           0.62
                                 2131
```

accuracy 0.74 10537 macro avg 0.73 0.67 0.70 10537 weighted avg 0.74 0.74 0.74 10537

In []:

MLP

)

```
In [164]:
    from sklearn.neural_network import MLPClassifier

    mlp_model = MLPClassifier(hidden_layer_sizes=(128, 64), max_iter=500, ran
    dom_state=42)
    mlp_model.fit(X_train, y_train_le)

    y_pred_mlp = mlp_model.predict(X_test)
    print("Neural Network Results:")
    print(classification_report( y_test_le, y_pred_mlp))
    print("Accuracy:", accuracy_score( y_test_le, y_pred_mlp))
```

Neural Network Results:

	precision	recall	f1-score	support
0	0.80	0.73	0.76	768
1	0.76	0.72	0.74	556
2	0.65	0.72	0.68	3081
3	0.87	0.91	0.89	3269
4	0.64	0.62	0.63	215
5	0.57	0.49	0.52	517
6	0.64	0.55	0.59	2131
accuracy			0.73	10537
macro avg	0.70	0.68	0.69	10537
weighted avg	0.73	0.73	0.73	10537

Accuracy: 0.7310429913637658

In []:

LSTM

```
In [97]:
         import tensorflow as tf
         from tensorflow.keras.preprocessing.text import Tokenizer
         from tensorflow.keras.preprocessing.sequence import pad_sequences
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout
         max_words=5000
         max_sequence_length=50
         tokenizer = Tokenizer(num_words=max_words)
         tokenizer.fit_on_texts(X_text)
         X_text_sequences = tokenizer.texts_to_sequences(X_text)
         X_text_padded = pad_sequences(X_text_sequences, maxlen=max_sequence_lengt
         h,padding='post')
         X_train_text, X_test_text, y_train_lstm, y_test_lstm = train_test_split(
             X_text_padded, y, test_size=0.2, random_state=42, stratify=y
         y_train_le_lstm=le.fit_transform(y_train_lstm)
         y_test_le_lstm=le.fit_transform(y_test_lstm)
         model = Sequential([
             Embedding(input_dim=5000, output_dim=128, input_length=max_sequence_l
         ength),
             LSTM(128, return_sequences=False),
             Dropout(0.5),
             Dense(64, activation='relu'),
             Dropout(0.5),
             Dense(len(le.classes_), activation='softmax')
         1)
         model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', m
         etrics=['accuracy'])
         model.fit(X_train_text, y_train_le_lstm, validation_data=(X_test_text, y_
         test_le_lstm), epochs=5, batch_size=32)
        y_pred_lstm = model.predict(X_test_text)
         y_pred_lstm_classes = y_pred_lstm.argmax(axis=1)
         print("LSTM Results:")
         print(classification_report(y_test_le_lstm, y_pred_lstm_classes))
```

```
Epoch 1/5
606 - accuracy: 0.5583 - val_loss: 0.9571 - val_accuracy: 0.6082
Epoch 2/5
162 - accuracy: 0.6569 - val_loss: 0.8823 - val_accuracy: 0.6750
Epoch 3/5
7880 - accuracy: 0.7186 - val_loss: 0.8032 - val_accuracy: 0.7170
Epoch 4/5
856 - accuracy: 0.7594 - val_loss: 0.7677 - val_accuracy: 0.7253
Epoch 5/5
069 - accuracy: 0.7884 - val_loss: 0.7622 - val_accuracy: 0.7295
330/330 [============== ] - 9s 25ms/step
LSTM Results:
         precision
               recall f1-score
                              support
       0
            0.65
                  0.80
                         0.72
                                768
            0.77
                         0.73
       1
                  0.69
                                556
       2
            0.70
                  0.61
                         0.66
                               3081
       3
            0.90
                  0.90
                         0.90
                               3269
       4
            0.75
                  0.33
                         0.45
                                215
       5
            0.44
                  0.49
                         0.47
                                517
            0.62
                  0.73
                         0.67
                               2131
  accuracy
                         0.73
                               10537
 macro avg
            0.69
                  0.65
                         0.66
                               10537
```

0.73

10537

BERT + XGBoost

weighted avg

0.73

0.74

Machine Learning Pipeline

The pipeline consists of:

- 1. Sampling & Balancing the Data (to avoid class imbalance issues)
- 2. Embedding Text using BERT (to convert text into meaningful numerical representations)
- 3. Training an XGBoost Classifier (a powerful gradient boosting algorithm)

#

```
In [70]:
         import tensorflow_hub as hub
         import tensorflow as tf
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import LabelEncoder
         from xgboost import XGBClassifier
         from sklearn.metrics import accuracy_score, classification_report
         from sklearn.utils import resample
         import tensorflow as tf
         import tensorflow_hub as hub
         import tensorflow_text as text
         from sklearn.utils import resample
         import os
         os.environ['TF_USE_LEGACY_KERAS'] = '1'
         import warnings
         warnings.filterwarnings('ignore')
```

```
In [71]: df.shape

Out[71]: (52681, 4)
```

```
1/29/25, 11:11 AM
   In [72]:
             label_ordered = df['status'].value_counts().index
             label_ordered = {k:i for i,k in enumerate(label_ordered,0)}
             label_ordered
    Out[72]:
             {'Normal': 0,
              'Depression': 1,
              'Suicidal': 2,
              'Anxiety': 3,
              'Bipolar': 4,
              'Stress': 5,
```

'Personality disorder': 6}

```
In [73]:
         df['status'] = df['status'].map(label_ordered)
         df.head()
```

Out[73]:

	status	cleaned_statement	num_of_characters	num_of_words
0	3	oh gosh	10	3
1	3	trouble sleeping confused mind restless heart	64	10
2	3	wrong back dear forward doubt stay restless re	78	14
3	3	shifted focus something still worried	61	11
4	3	restless restless month boy mean	72	14

```
In [74]: print(df['status'].value_counts())
```

```
status
0
     16343
1
     15404
2
     10652
3
      3841
4
      2777
5
      2587
6
      1077
Name: count, dtype: int64
```

If we train a model on this dataset:

- The model might always predict the majority class (0: Legitimate) because it appears more frequently.
- Accuracy might be high, but the model fails to detect fraudulent cases (1).
- This leads to a biased and unreliable model

Step Process Purpose 1 Identify Class Distribution

- Count the number of samples in each class
- Detect imbalance
- 2 Resample Data
 - Apply oversampling or undersampling
 - · Balance the dataset
- 3 Train Model
 - Use the balanced dataset for training
 - Improve accuracy & fairness

```
In [75]:
    df_sample = df.sample(n=20000,random_state=2024)
    majority_size = len(df_sample[df_sample['status']==0])
    majority_size
```

Out[75]: 6140

```
In [76]:
    from sklearn.utils import resample

    def resampling_dfs(df):
        resample_minority = resample(df, replace=True, n_samples=majority_siz
        e, random_state= 768)
        return resample_minority
```

In [77]: df_sample

Out[77]:

	status	cleaned_statement	num_of_characters	num_of_words
43491	0	caitlinaudrey awww suck going sydney one	60	11
46017	4	feel like killing still one listens convinced	1355	259
24191	2	dl hellome hellodl hello know saydl okay dl so	642	101
6893	0	body ache	9	2
40455	1	feel like believe really going trial run see g	150	37
45045	0	argh stop yawning	22	4
17141	2	people love say suicide selfish way around sel	229	44
42853	0	riskyrevenge wait sick	27	4
40028	1	long story sorry ex broke year ago remained fr	7747	1726
9286	2	suffering must continue way	45	9

20000 rows × 4 columns

```
In [78]:
    df_sample_0 = resampling_dfs(df_sample[df_sample['status']==0])
    df_sample_1 = resampling_dfs(df_sample[df_sample['status']==1])
    df_sample_2 = resampling_dfs(df_sample[df_sample['status']==2])
    df_sample_3 = resampling_dfs(df_sample[df_sample['status']==3])
    df_sample_4 = resampling_dfs(df_sample[df_sample['status']==4])
    df_sample_5 = resampling_dfs(df_sample[df_sample['status']==5])
    df_sample_6 = resampling_dfs(df_sample[df_sample['status']==6])

    df_new =pd.concat([df_sample_0,df_sample_1,df_sample_2,df_sample_3,df_sample_4,df_sample_5,df_sample_6], axis=0).reset_index(drop=True)

    df_new['status'].value_counts()
```

Out[78]:

status

- 0 6140
- 1 6140
- 2 6140
- 3 6140
- 4 6140
- 5 6140
- 6 6140

Name: count, dtype: int64

```
In [79]: df_new
```

Out[79]:

	status	cleaned_statement	num_of_characters	num_of_words
0	0	secret achieving success success happen prepar	127	21
1	0	proud	10	2
2	0	seen far couple lizards	45	10
3	0	tell	31	6
4	0	welcome twitter	28	4
42975	6	interview anxiety job searching since august o	508	91
42976	6	trying make friend someone lot friends making	1216	238
42977	6	please hear success stories yall got share	70	13
42978	6	also want get rid avpd avoiding makes much sen	398	73
42979	6	hobbies comfortable sharing anyone hobbiesacti	105	15

42980 rows × 4 columns

```
In [81]:
    print("TF version:", tf.__version__)  # Should be 2.9, 2.10, 2.11, etc.
    print("Hub version:", hub.__version__) # ~0.12 or newer
    print("Text version:", text.__version__)
```

TF version: 2.9.0 Hub version: 0.16.1 Text version: 2.9.0

Why Use BERT for Text Embeddings?

- Machine learning models can't understand text directly. They need numerical representations.
- Traditional techniques (like TF-IDF or Word2Vec) have limitations in understanding context.
- BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model developed by Google that:
 - Understands contextual meaning by looking at words in both directions (left and right).
 - Is pre-trained on massive text corpora (Wikipedia, books, etc.), so it understands language better than older models.

What is Happening Here?

1. bert_preprocess:

- Handles tokenization, lowercasing, and adding special tokens (like [CLS] for classification tasks).
- · Converts text into a format BERT understands.

2. bert_encoder:

- Uses the BERT model to generate embeddings.
- Outputs 768-dimensional feature vectors for each input sentence.

```
In [82]:
    bert_preprocess = hub.KerasLayer(
        "https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3",
        name="bert_preprocess_layer"
    )
    bert_encoder = hub.KerasLayer(
        "https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/4",
        trainable=True,
        name="bert_encoder_layer"
    )
```

- Takes raw text input (text input).
- Uses BERT preprocessing (bert_preprocess) to prepare text.
- Passes the preprocessed text to BERT encoder (bert_encoder).
- Outputs pooled BERT embeddings (pooled_output), which are 768-dimensional vector representations of the entire sentence.

BERT provides two types of outputs:

- 1. sequence output → Word-level embeddings (useful for Named Entity Recognition).
- 2. pooled output → Sentence-level embeddings (useful for classification tasks).
- ★ Since we are doing text classification, we use pooled output, which represents the entire sentence.

```
In [84]:
    text_input = tf.keras.layers.Input(shape=(), dtype=tf.string, name='tex
    t')
    preprocessed_text = bert_preprocess(text_input)
    encoder_outputs = bert_encoder(preprocessed_text)
    pooled_output = encoder_outputs["pooled_output"]
    embedding_model = tf.keras.Model(inputs=text_input, outputs=pooled_output)
    t)
```

- The dataset is split into training (X train) and testing (X test) sets.
- The text data is passed through the BERT model (embedding model.predict()).
- BERT converts each text statement into a 768-dimensional vector.
- These vectors (train embeddings and test embeddings) are now ready for classification.

Why Do We Use BERT Before XGBoost?

- XGBoost does not understand text; it requires numerical input.
- BERT converts text into numerical embeddings, making it possible to train XGBoost.

→ Without BERT, we would have to use TF-IDF or Word2Vec, which do not capture deep contextual meaning like BERT does.

- ? Why Use XGBoost for Text Classification?
- XGBoost (Extreme Gradient Boosting) is one of the most powerful tree-based machine learning models.
- It is used for structured data and tabular data.
- Better than traditional ML models like Logistic Regression and SVM because:
- Handles non-linearity and feature interactions automatically.
- Uses gradient boosting, meaning it learns iteratively and corrects mistakes at each step.
- · Optimized for speed and handles missing values well.

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      validation_0-mlogloss:0.20885
[493]
      validation_0-mlogloss:0.20852
[494]
      validation_0-mlogloss:0.20823
[495]
      validation_0-mlogloss:0.20791
       validation_0-mlogloss:0.20762
[496]
[497]
      validation_0-mlogloss:0.20725
       validation_0-mlogloss:0.20690
[498]
       validation_0-mlogloss:0.20659
[499]
```

In [87]:

• Classification Report:

	precision	recall	f1-score	support
0	0.94	0.95	0.94	1260
1	0.87	0.78	0.83	1220
2	0.86	0.87	0.87	1187
3	0.97	0.98	0.98	1252
4	0.97	1.00	0.98	1215
5	0.96	1.00	0.98	1210
6	0.99	1.00	1.00	1252
accuracy			0.94	8596
macro avg	0.94	0.94	0.94	8596
weighted avg	0.94	0.94	0.94	8596

✓ Test Accuracy: 0.9404