Personality-Constructed Chatting Application

Implementing a Personality-Based Chatbot by Testing Different AI Models with the MBTI Dataset

A Project Report

Completed By:

ABHIRAJ GHOSE (E23CSEU0014)

PALLAV SHARMA (E23CSEU0022)

Submitted To:

SCHOOL OF COMPUTER SCIENCE ENGINEERING AND TECHNOLOGY, BENNETT UNIVERSITY

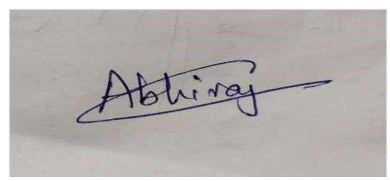
GREATER NOIDA, 201310, UTTAR PRADESH, INDIA

15 November 2024

DECLARATION

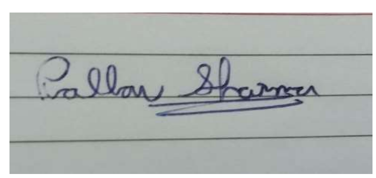
We hereby declare that the work which is being presented in the report entitled “Personality-Constructed Chatting Application”, is an authentic record of our own work carried out under the guidance of Ms. Dipika Jain during the period from August 2024 to November 2024 at the School of Computer Science and Engineering and Technology, Bennett University, Greater Noida.

The matters and the results presented in this report has not been submitted by us for the award of any other degree elsewhere.



Abhiraj Ghose

(Enroll. No. E23CSEU0014)



Pallav Sharma

(Enroll. No. E23CSE0022)

TABLE OF CONTENTS

1. INTRODUCTION

- **This project aims to create a personality based chatbot using the most advanced Natural Language Processing (NLP) models.**

- **The chatbot is intended to predict users' MBTI personality types by analysing their text input, then generating insights.**

- **The project combines transformer models (such as BERT) with a chatbot interface using Groq's APIs for real time interaction with the user.**

1.1 Problem Description

Personality assessments in the field of psychology such as the Myers Briggs Type Indicator (MBTI) are used to understand different personality traits. The MBTI assessment has traditionally been a questionnaire that users complete in order to find out their own MBTI Personality Trait. Unfortunately, it's a time consuming, subjective and biased process.

Problem Statement:

- **How can we automate the process of predicting personality types using textual data?**
- **How can we provide users with real-time, interactive feedback on their personality traits through a chatbot interface?**

This project aims to solve these issues by implementing an NLP model that predicts MBTI personality types based on user-generated text, making the process faster and more scalable.

1.2 Background

The Myers-Briggs Type Indicator (MBTI) is a popular personality assessment tool based on Carl Jung's theories of psychological types. The MBTI divides people into 16 personality types according to preference in 4 dimensions:

- **Introversion (I) vs. Extraversion (E)**
- **Sensing (S) vs. Intuition (N)**
- **Thinking (T) vs. Feeling (F)**
- **Judging (J) vs. Perceiving (P)**

Mixing and Matching these dimensions of Personality Traits creates a total of 16 Personality Types, which are ISTJ, ISFJ, INFJ, INTJ, ISTP, ISFP, INFP, INTP, ESTP, ESFP, ENFP, ENTP, ESTJ, ESFJ, ENFJ and ENTJ. The use of written content users posts on social media and otherwise has been a popular way to use users to assess their personality. Using recent advances in NLP, particularly transformer models like BERT, predicting personality traits precisely from text is now possible.

Technological Context:

- **Transformer models such as BERT, DeBERTa, and RoBERTa have revolutionized NLP tasks, achieving state-of-the-art results in text classification, sentiment analysis, and named entity recognition.**
- **The integration of APIs like Groq's provides a seamless way to deploy interactive chatbots, enhancing user engagement and experience.**

1.3 Objectives

The primary objectives of this project are:

1. **Personality Prediction:**
   - **To predict MBTI personality types based on users' text input using fine-tuned transformer models.**
2. **Model Optimization:**
   - **To fine-tune the selected NLP models for optimal performance, utilizing techniques like hyperparameter tuning.**
3. **Chatbot Integration:**
   - **To create an engaging and interactive chatbot using Groq's API that provides users with real-time feedback on their personality traits.**
4. **User Interaction and Insights:**
   - **To enhance user engagement by delivering personalized insights based on the predicted personality type.**
5. **Performance Evaluation:**
   - **To evaluate the effectiveness of the model using metrics such as accuracy, precision, recall, F1 score, and ROC-AUC.**

1.4 Scope of the Project

The scope of this project extends beyond simple personality prediction. The chatbot system is designed to:

- **Provide real-time predictions of MBTI personality types based on any given text input.**
- **Support interactive conversations with users, making the predictions engaging and insightful.**
- **Offer potential applications in areas like mental health, career counseling, and social media analysis.**

2. PROJECT OUTLINE AND DESIGN

This project focuses on creating an automated chatbot capable of predicting MBTI personality types from user-provided text.

The system leverages state-of-the-art NLP models and integrates an API-based chatbot interface for interactive feedback.

2.1 Tools and Technologies

The project incorporates various tools and technologies to achieve efficient data processing, model training, and chatbot deployment:

- **Programming Language: Python was chosen due to its robust ecosystem for machine learning and NLP tasks.**
- **Deep Learning Framework: PyTorch was utilized for implementing and fine-tuning the transformer models. It offers dynamic computation graphs and GPU support for efficient training.**
- **Libraries:**
  - **Hugging Face Transformers: Provides access to pre-trained models like BERT, DeBERTa, RoBERTa, and DistilGPT2. This library simplifies model fine-tuning and deployment.**
  - **Scikit-learn: Used for data preprocessing tasks, such as label encoding, feature selection, and evaluation metrics.**
  - **Pandas and NumPy: Employed for data manipulation and statistical analysis.**
  - **Matplotlib and Seaborn: Utilized for visualizing data distributions, performance metrics, and evaluation results.**
- **API Integration:**
  - **Groq API: Used for building an interactive chatbot that communicates with the user and provides personality insights based on predictions from the fine-tuned model.**

2.2 Programming Language, Libraries, and Models Used

The project utilizes several pre-trained transformer models for personality prediction. Here's a breakdown of the programming language, key libraries, and models:

- **Programming Language:**
  - **Python: The primary language used, chosen for its versatility and extensive support for NLP and machine learning tasks.**

Libraries:

- PyTorch: Used for implementing deep learning models and handling GPU acceleration.
- Transformers (Hugging Face): Provides an extensive collection of pre-trained models and utilities for text tokenization and model fine-tuning.
- Scikit-learn: Assists in preprocessing tasks and evaluating model performance.
- Pandas and NumPy: Facilitate efficient data handling and numerical computations.

- **Models:**
    - BERT (Bidirectional Encoder Representations from Transformers):
        - Chosen for its bidirectional understanding of text, making it effective in capturing context for personality prediction.
    - DeBERTa (Decoding-enhanced BERT with Disentangled Attention):
        - Selected for its advanced attention mechanism, which enhances performance on complex NLP tasks.
    - RoBERTa (A Robustly Optimized BERT Pretraining Approach):
        - Used for its improved training strategy, offering better generalization capabilities.
    - DistilGPT2:
        - Implemented for generating coherent responses in the chatbot, allowing dynamic and engaging user interactions.

2.3 Justification for Model Selection

The choice of models is based on their performance, versatility, and ability to capture linguistic nuances effectively. Here's why each model was chosen:

- **BERT:**
    - Well-suited for text classification tasks due to its bidirectional context encoding. It captures the meaning of words in context, making it ideal for personality prediction.
- **DeBERTa:**
    - Incorporates disentangled attention, which improves the model's understanding of complex text dependencies. It is especially useful for tasks requiring a deeper semantic understanding.

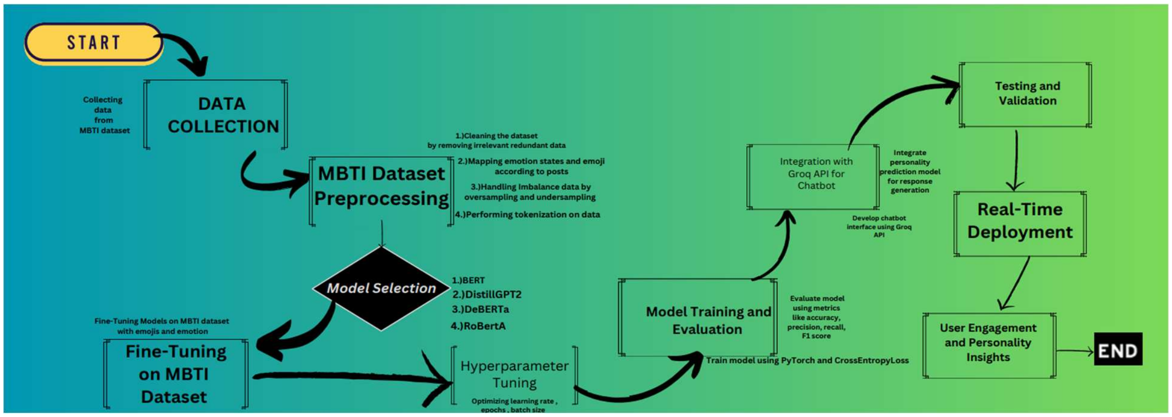
- **RoBERTa:**
    - **An optimized version of BERT, trained on more data without the Next Sentence Prediction objective. It offers enhanced performance on a wide range of NLP benchmarks, making it a strong candidate for this project.**
- **DistilGPT2:**
    - **A distilled version of GPT-2, chosen for its efficiency in text generation. It retains most of the capabilities of GPT-2 while being faster and less resource-intensive, making it suitable for generating chatbot responses.**

2.4 System Architecture

The system architecture is designed to handle both personality prediction and real-time chatbot interaction. Below is a high-level overview of the architecture:

1. **Data Layer:**
    - **The MBTI dataset is pre-processed and stored for efficient access during model training.**
2. **Model Layer:**
    - **Fine-tuned transformer models (BERT, DeBERTa, RoBERTa) are employed for personality prediction.**
    - **DistilGPT2 is used for generating conversational responses.**
3. **Chatbot Interface:**
    - **The chatbot is integrated using the Groq API, which allows users to interact with the system via a user-friendly interface.**
    - **User input is passed to the personality prediction model, and the predicted MBTI type is used to tailor the chatbot's responses.**
4. **Feedback and Insights Layer:**
    - **The chatbot provides personalized feedback based on the predicted personality type.**
    - **Insights about the user's personality traits and cognitive preferences are generated and presented interactively.**

2.5 Methodology



The methodology of the personality-based chatbot project outlines the step-by-step process followed to build an effective and interactive system for MBTI personality prediction and user engagement. It covers data preparation, model training, fine-tuning, integration of the chatbot, and testing.

Step 1: Data Collection and Preprocessing

- **Dataset:**
  - **The project utilizes a publicly available MBTI dataset containing user-generated text labelled with the corresponding MBTI personality types (e.g., INTJ, ENFP). The dataset includes a diverse range of social media posts, which provide the linguistic features needed for accurate personality prediction.**
- **Data Cleaning:**
  - **Preprocessing is a critical step to ensure data quality. The text data was cleaned by:**
    - **Removing special characters, URLs, and unnecessary punctuation.**
    - **Retaining emojis as they can carry important emotional context, which may help in personality assessment.**
- **Tokenization:**
  - **The text data was tokenized using the BERT tokenizer, which employs the Word-Piece algorithm. This step splits the text into sub-word units, allowing the model to handle both common and rare words effectively.**
- **Imbalance Handling:**
  - **The MBTI dataset often exhibits class imbalance, where certain personality types are underrepresented. To address this, techniques like oversampling**

of minority classes or class weighting were applied to ensure a balanced training process.

Step 2: Model Selection and Fine-Tuning

- **Model Selection:**
  - **Several state-of-the-art transformer models were chosen for this task, including BERT, DeBERTa, and RoBERTa. These models are known for their powerful language understanding capabilities and their success in various text classification tasks.**
- **Fine-Tuning:**
  - **The selected models, which were pre-trained on large text corpora, were fine-tuned on the MBTI dataset to adapt them to the specific task of personality prediction. Fine-tuning involves training the models on the labeled dataset while adjusting the weights to optimize performance for the new task.**
- **Hyperparameter Tuning:**
  - **The performance of the models was further improved through hyperparameter tuning. Techniques like grid search and random search were used to find the optimal values for learning rate, batch size, and the number of epochs.**

Step 3: Chatbot Integration Using Groq API

- **Chatbot Development:**
  - **A chatbot interface was developed using the Groq API to allow users to interact with the system in real time. The chatbot serves as the main interface for users to input their text and receive personality feedback.**
- **Model Integration:**
  - **The fine-tuned transformer model for personality prediction was integrated into the chatbot system. When a user provides input, the text is processed by the model to predict the user's MBTI personality type.**

Step 4: Testing and Validation

- **Evaluation Metrics:**
  - **The performance of the model was evaluated using standard metrics like accuracy, precision, recall, F1 score, and ROC-AUC. These metrics helped assess how well the model generalized to new, unseen data.**
- **Testing the Chatbot:**

- The chatbot was rigorously tested to ensure that it could handle a variety of user inputs and maintain coherent, contextually appropriate responses. Various scenarios were simulated to validate the chatbot's ability to engage users effectively.

Step 5: Deployment and User Interaction

- **Real-Time Deployment:**
  - The system was deployed in a real-time environment, allowing users to interact with the chatbot and receive instant feedback on their personality type. The integration with Groq's API facilitated seamless interaction and response generation.

---

3. RESULTS AND ANALYSIS

3.1 Model Performance and Evaluation Metrics

The performance of the personality prediction model was evaluated using several metrics on the test dataset:

Accuracy: The percentage of correct predictions made by the model across all samples.

Precision, Recall, and F1 Score

3.2 Comparative Analysis of Models

Model	Accuracy	Precision	Recall	F1-score
BERT	91%	87%	82%	84%
DeBERTa	0.3%	0%	0.6%	0%
RoBERTa	0.3%	0.9%	0.3%	0.3%
DistillGPT2	0.3%	0.4%	0.6%	0.1%

BERT showed the best performance, indicating that its enhanced training strategy provided a significant advantage for personality classification.

3.3 Limitations and Interpretation of Results

- **Contextual Understanding:**
  - While the models performed well overall, they struggled with capturing nuanced or sarcastic text, which sometimes led to incorrect predictions.

- **Imbalanced Classes:**
    - **Despite efforts to balance the dataset, certain personality types and emotions with fewer samples had lower prediction accuracy.**

4. CONCLUSION AND FUTURE WORK

4.1 Summary, Recommendations, and Real-World Applications

Summary:

- **This project successfully developed a personality-based chatbot using state-of-the-art transformer models (BERT, DeBERTa, RoBERTa). The fine-tuned models were integrated into a chatbot interface using Groq's API, allowing real-time interaction and personalized feedback for users.**
- **The results demonstrated that the models could somewhat accurately predict MBTI personality types based on text input, with BERT achieving the best overall performance.**

Recommendations:

- **Further optimization of hyperparameters and experimenting with additional transformer models (e.g., XLNet) could further improve accuracy.**
- **Incorporating additional features such as sentiment analysis could enhance the chatbot's responses and user engagement.**

Real-World Applications:

- **The chatbot could be applied in areas such as mental health support, career counselling, and social media analysis, providing personality insights based on user interactions.**

4.2 Future Enhancements

1. **Dataset Expansion:**
    - **Expanding the dataset with more diverse text samples could improve the model's generalization capabilities.**
2. **Multi-Modal Integration:**

- Incorporating voice and facial emotion analysis could add another layer of personality detection, enhancing the chatbot's capabilities.

3. **Enhanced Chatbot Coherence:**
    - Improving the conversational abilities of the chatbot using more advanced text generation models like GPT-4 could provide a more natural user experience.

4.3 Scalability and Deployment

- The current system can be scaled using cloud-based solutions (e.g., AWS, Google Cloud) for real-time deployment, allowing wider accessibility and faster response times.

5. APPENDICES

5.1 Code Snippets and Algorithms

- Sample code for data preprocessing, model training, and chatbot integration is provided.

Cleaning the Posts

```python
import pandas as pd
import re
from tqdm import tqdm
from collections import Counter
import numpy as np
from sklearn.utils import resample
import matplotlib.pyplot as plt
from transformers import pipeline

emotion_classifier = pipeline("text-classification", model="j-hartmann/emotion-english-distilroberta-base", device=0)

def clean_text(text):
    """Clean the input text by removing URLs, mentions, hashtags, and non-alphabetical characters."""
    text = re.sub(r"http\S+|www\S+|https\S+", "", text, flags=re.MULTILINE)
    text = re.sub(r'\@\w+|\#|\d+', '', text)
    text = re.sub(r"[^a-zA-Z\s]", "", text)
    text = re.sub(r"\s+", " ", text).strip()
    return text
```

Dividing posts into chunks and assigning emotions on the average score

```python
def split_text_into_chunks(text, max_length=512):
    words = text.split()
    chunks = []
    current_chunk = []

    for word in words:
        current_chunk.append(word)
        if len(' '.join(current_chunk)) > max_length:
            chunks.append(' '.join(current_chunk[:-1]))
            current_chunk = [current_chunk[-1]]

    if current_chunk:
        chunks.append(' '.join(current_chunk))

    return chunks

def assign_emotion(post):
    chunks = split_text_into_chunks(post)
    emotion_predictions = emotion_classifier(chunks)
    emotion_labels = [pred['label'] for pred in emotion_predictions]
    most_frequent_emotion = Counter(emotion_labels).most_common(1)[0][0]

    emotion_scores = [pred['score'] for pred in emotion_predictions]
    emotion_score_map = {}
    for label, score in zip(emotion_labels, emotion_scores):
        if label in emotion_score_map:
            emotion_score_map[label].append(score)
        else:
            emotion_score_map[label] = [score]

    average_scores = {label: np.mean(scores) for label, scores in emotion_score_map.items()}
    final_predicted_emotion = max(average_scores, key=average_scores.get)

    return final_predicted_emotion
```

Mapping emotions to an emoji

```python
def assign_emoji(emotion):
    emoji_map = {
        'anger': '😡',
        'fear': '😱',
        'joy': '😊',
        'love': '❤️',
        'sadness': '😢',
        'surprise': '😲',
        'neutral': '😐'
    }
    return emoji_map.get(emotion.lower(), '🤷')
```

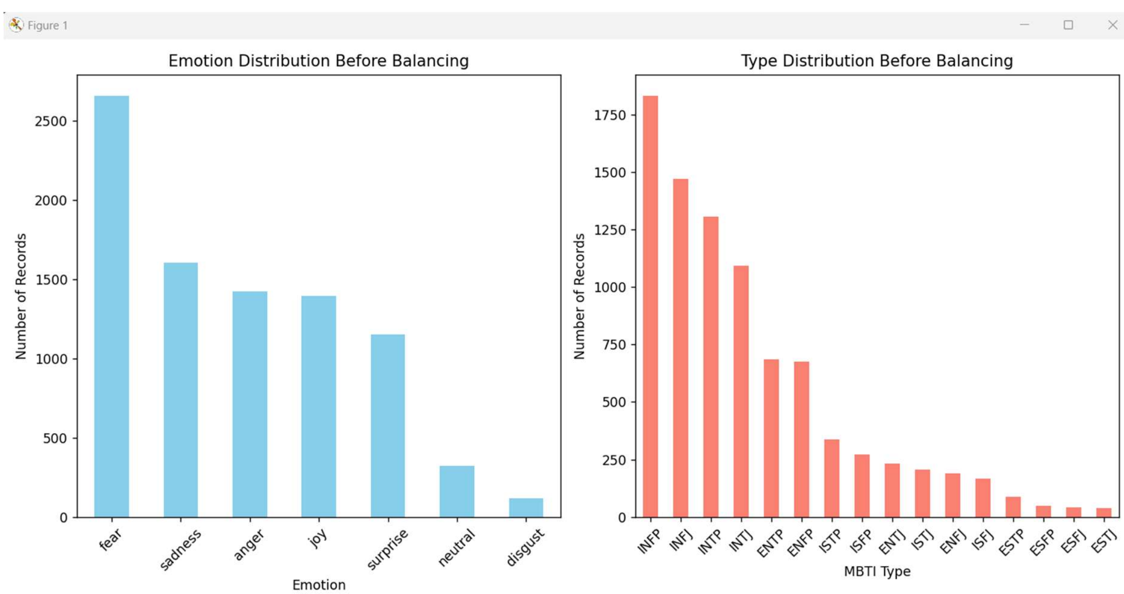
Balancing the dataset by oversampling and under-sampling

```python
print("Balancing the dataset by oversampling underrepresented emotions and types...\n")

max_count_emotion = df['emotion'].value_counts().max()
max_count_type = df['type'].value_counts().max()

balanced_df = pd.concat([
    resample(df[df['emotion'] == emotion],
             replace=True,
             n_samples=max_count_emotion,
             random_state=42)
    for emotion in df['emotion'].unique()
])

balanced_df = pd.concat([
    resample(balanced_df[balanced_df['type'] == type_],
             replace=True,
             n_samples=max_count_type,
             random_state=42)
    for type_ in balanced_df['type'].unique()
])

balanced_df = balanced_df.sample(frac=1, random_state=42).reset_index(drop=True)
```

5.2 Additional Graphs and Visualizations

- **Additional charts showing the distribution of text lengths, word frequencies, and confusion matrices for each model AND Dataset.**

Dataset Visualisation



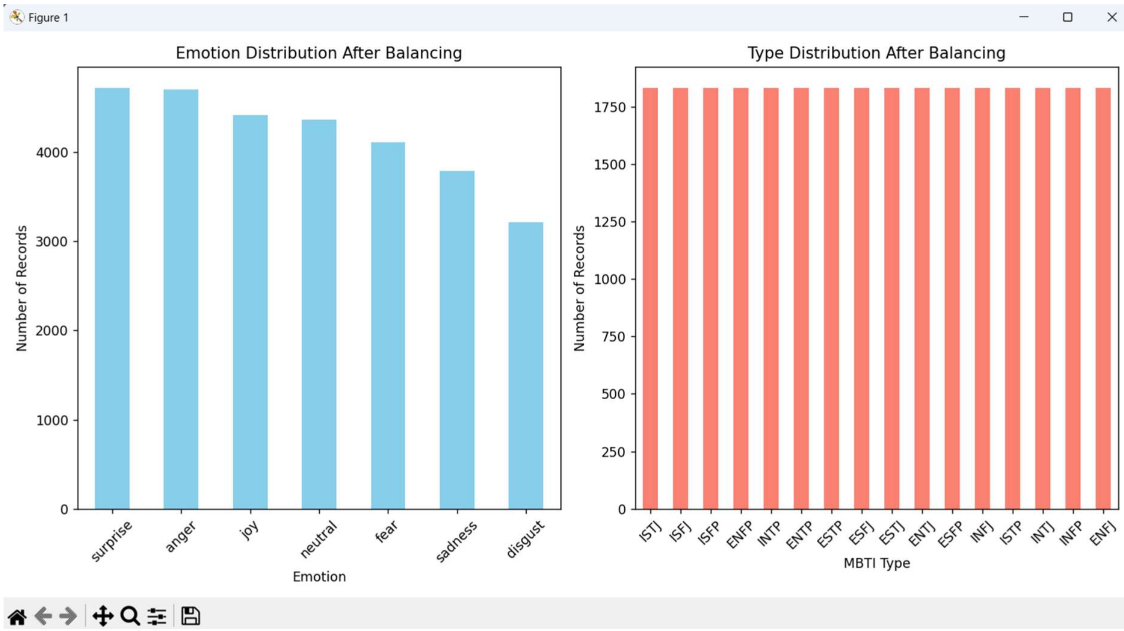


Figure 1
Emotion Distribution After Balancing
Number of Records
Emotion
surprise
anger
joy
neutral
fear
sadness
disgust
Type Distribution After Balancing
Number of Records
MBTI Type
ISTJ
ISFJ
ISFP
ENFP
INTP
ENTP
ESTP
ESFJ
ESTJ
ENTJ
ESFP
INFJ
ISTP
INTJ
INFP
ENFJ

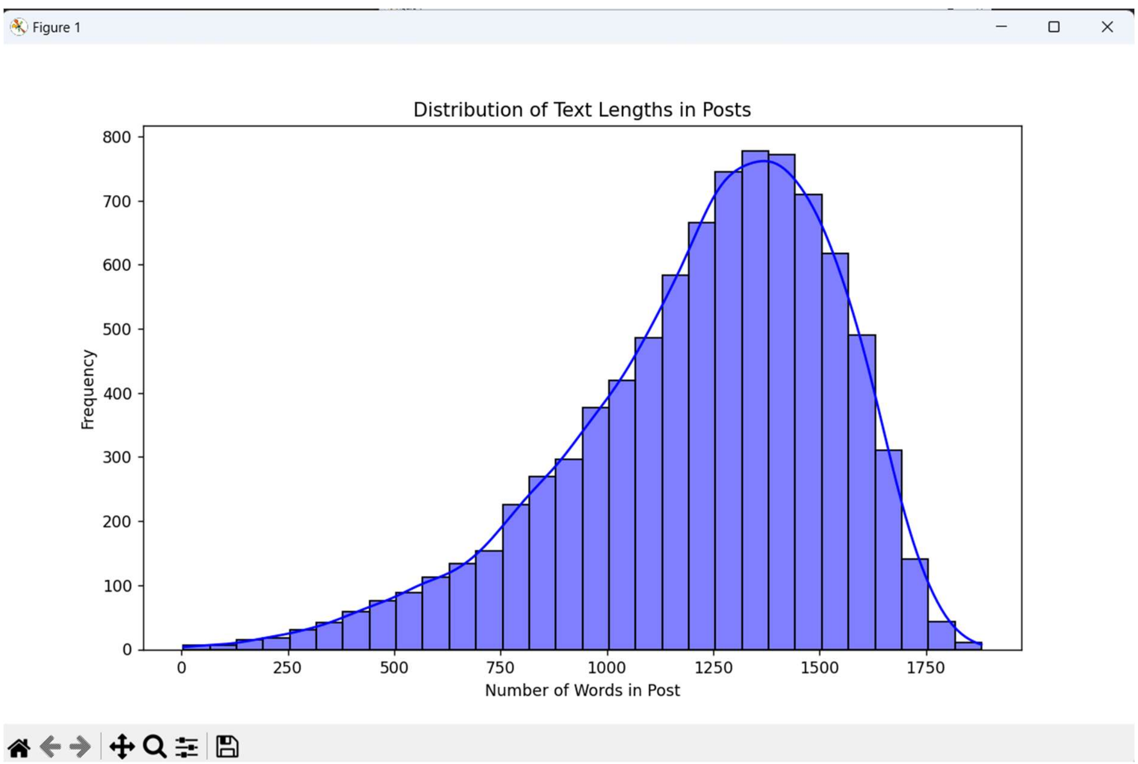


Figure 1
Distribution of Text Lengths in Posts
Frequency
Number of Words in Post

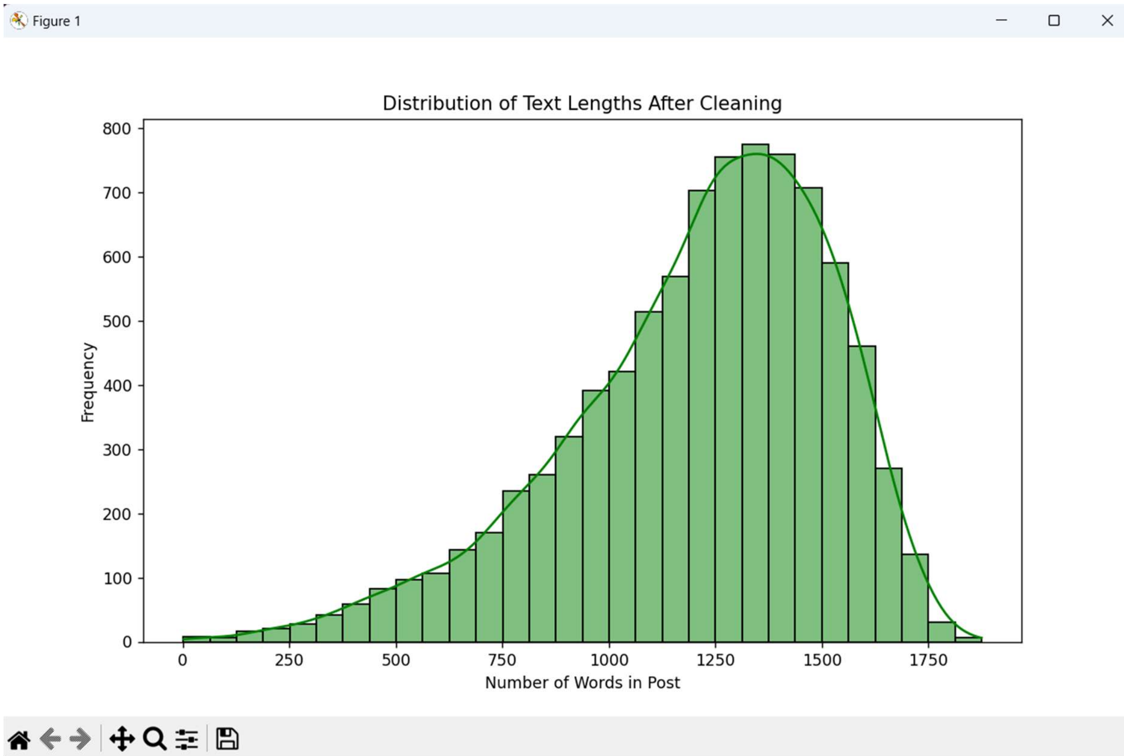
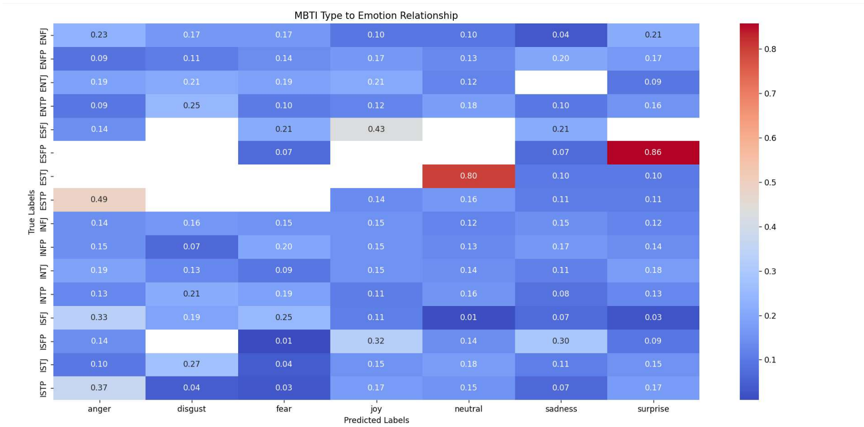


Figure 1
Distribution of Text Lengths After Cleaning
Frequency
Number of Words in Post
0
100
200
300
400
500
600
700
800
0
250
500
750
1000
1250
1500
1750

5.3 List of Figures and Tables

- **BERT**



Generating classification reports for all outputs...

Classification Report for MBTI Type:

	precision	recall	f1-score	support
ENFJ	0.88	0.87	0.87	84
ENFP	0.92	0.89	0.91	247
ENTJ	0.89	0.89	0.89	114
ENTP	0.92	0.93	0.92	300
ESFJ	0.75	0.63	0.69	19
ESFP	0.86	0.48	0.62	25
ESTJ	0.67	0.53	0.59	15
ESTP	0.84	0.89	0.86	36
INFJ	0.93	0.92	0.93	616
INFP	0.92	0.93	0.93	733
INTJ	0.89	0.94	0.91	500
INTP	0.91	0.92	0.92	643
ISFJ	0.82	0.84	0.83	74
ISFP	0.89	0.89	0.89	108
ISTJ	0.84	0.77	0.80	82
ISTP	0.93	0.86	0.89	130
accuracy			0.91	3726
macro avg	0.87	0.82	0.84	3726
weighted avg	0.91	0.91	0.91	3726

Classification Report for Emotions:

	precision	recall	f1-score	support
anger	0.72	0.78	0.75	528
disgust	1.00	1.00	1.00	534
fear	0.62	0.52	0.57	541
joy	0.77	0.79	0.78	548
neutral	0.99	1.00	0.99	518
sadness	0.68	0.64	0.66	538
surprise	0.79	0.87	0.83	519
accuracy			0.80	3726
macro avg	0.79	0.80	0.80	3726
weighted avg	0.79	0.80	0.79	3726

Classification Report for Emojis:

	precision	recall	f1-score	support
😊	0.76	0.80	0.78	548
😳	0.99	1.00	0.99	518
	0.72	0.77	0.75	528

Analyzing relationships between MBTI types and predictions...

Top predicted emotions associated with each MBTI type:

pred_emotion / pred_type	anger	disgust	fear	joy	neutral	sadness	surprise
ENFJ	0.361446	0.168675	0.024096	0.156627	0.096386	NaN	0.192771
ENFP	0.091667	0.108333	0.150000	0.175000	0.116667	0.179167	0.179167
ENTJ	0.149123	0.192982	0.078947	0.236842	0.131579	0.078947	0.131579
ENTP	0.135314	0.250825	0.105611	0.112211	0.181518	0.059406	0.155116
ESFJ	0.375000	NaN	0.187500	0.312500	0.062500	NaN	0.062500
ESFP	NaN	NaN	0.357143	NaN	NaN	0.142857	0.500000
ESTJ	0.083333	NaN	0.083333	0.083333	0.500000	NaN	0.250000
ESTP	0.289474	NaN	0.052632	0.210526	0.184211	0.131579	0.131579
INFJ	0.121113	0.166939	0.122750	0.166939	0.121113	0.178396	0.122750
INFP	0.138024	0.067659	0.186739	0.150203	0.133965	0.188092	0.135318
INTJ	0.155009	0.128544	0.105860	0.141777	0.143667	0.128544	0.196597
INTP	0.132921	0.210201	0.120556	0.120556	0.157651	0.102009	0.156105
ISFJ	0.513158	0.184211	0.026316	0.184211	0.039474	0.026316	0.026316
ISFP	0.074074	NaN	NaN	0.314815	0.138889	0.370370	0.101852
ISTJ	0.186667	0.266667	0.040000	0.026667	0.173333	0.080000	0.226667
ISTP	0.330579	0.049587	0.082645	0.165289	0.165289	0.008264	0.198347

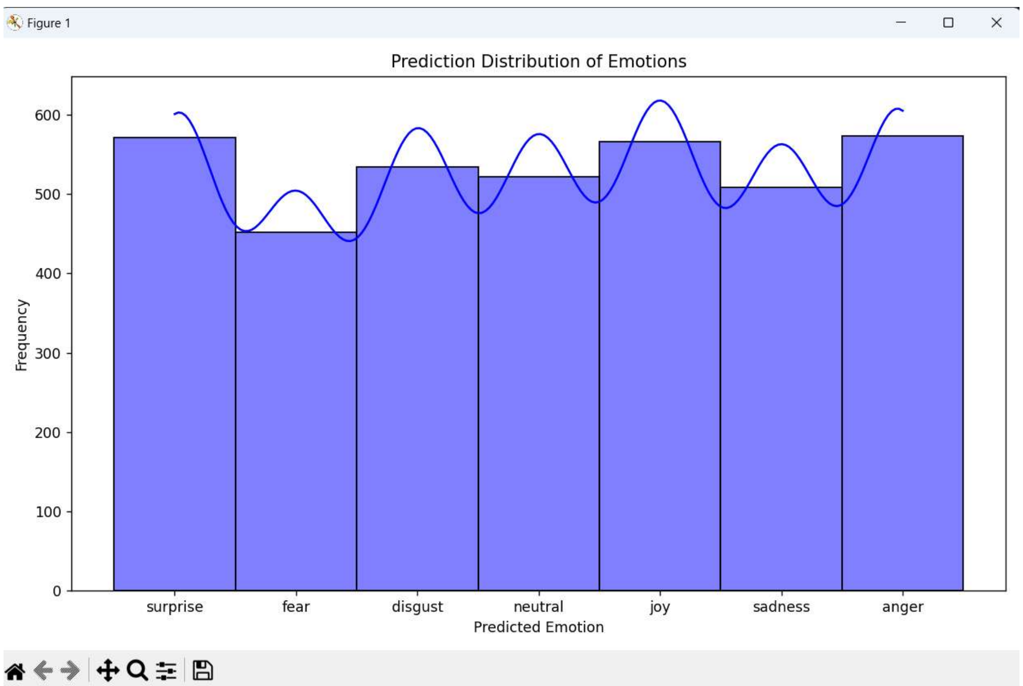


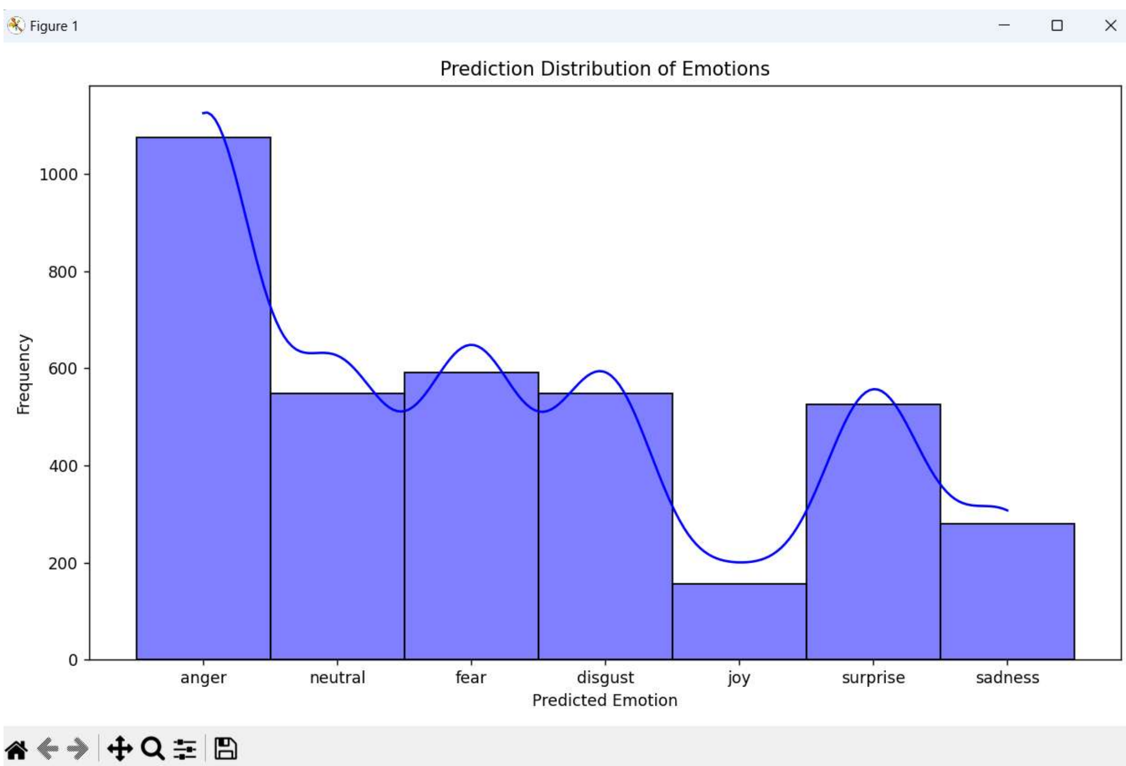
Figure 1
Prediction Distribution of Emotions
Frequency
0
100
200
300
400
500
600
surprise
fear
disgust
neutral
joy
sadness
anger
Predicted Emotion

- **RoBERTa**

```
Generating classification reports for all outputs...

Classification Report for MBTI Type:
              precision    recall  f1-score   support

        ENFJ       0.01      0.07      0.01        84
        ENFP       0.00      0.00      0.00       247
        ENTJ       0.09      0.02      0.03       114
        ENTP       0.00      0.00      0.00       300
        ESFJ       0.00      0.00      0.00        19
        ESFP       0.00      0.00      0.00        25
        ESTJ       0.00      0.00      0.00        15
        ESTP       0.02      0.03      0.02        36
        INFJ       0.03      0.01      0.02       616
        INFP       0.03      0.01      0.01       733
        INTJ       0.91      0.14      0.24       500
        INTP       0.23      0.01      0.02       643
        ISFJ       0.03      0.16      0.05        74
        ISFP       0.08      0.03      0.04       108
        ISTJ       0.01      0.06      0.01        82
        ISTP       0.00      0.00      0.00       130

    accuracy                           0.03      3726
   macro avg       0.09      0.03      0.03      3726
weighted avg       0.18      0.03      0.04      3726
```

```
Analyzing relationships between MBTI types and predictions...

Top predicted emotions associated with each MBTI type:
pred_emotion     anger   disgust      fear       joy   neutral   sadness  surprise
pred_type
ENFJ          0.275479  0.099899  0.118063  0.005045  0.166498  0.171544  0.163471
ENFP          0.261224  0.089796  0.257143  0.081633  0.191837  0.077551  0.040816
ENTJ               NaN  0.521739       NaN       NaN  0.086957       NaN  0.391304
ENTP          0.235110  0.128527  0.134796  0.200627  0.065831  0.056426  0.178683
ESFJ          0.200000  0.185714  0.285714       NaN  0.142857  0.028571  0.157143
ESFP               NaN  0.055556  0.092593  0.481481  0.018519  0.314815  0.037037
ESTJ          0.141361  0.361257  0.099476  0.026178  0.120419  0.041885  0.209424
ESTP          0.253968  0.015873  0.476190       NaN  0.174603  0.031746  0.047619
INFJ          0.110345  0.010345  0.200000  0.017241  0.268966  0.048276  0.344828
INFP          0.335294  0.129412  0.082353  0.035294  0.247059  0.094118  0.076471
INTJ          0.600000       NaN  0.026667       NaN  0.306667       NaN  0.066667
INTP          0.153846       NaN  0.076923  0.230769  0.307692       NaN  0.230769
ISFJ          0.708791  0.030220  0.217033       NaN  0.002747       NaN  0.041209
ISFP          0.027778  0.166667  0.138889       NaN  0.194444  0.027778  0.444444
ISTJ          0.345299  0.382906  0.073504  0.008547  0.179487  0.005128  0.005128
ISTP          0.031250  0.102679  0.406250  0.062500  0.022321  0.044643  0.330357

Top predicted emojis associated with each MBTI type:
pred_emoji          😊         😬         😡         😳         😱         😲        🤷‍♂️
pred_type
ENFJ       0.262361  0.137235  0.207871  0.004036  0.050454  0.023209  0.314834
ENFP       0.093878  0.171429  0.061224  0.048980  0.073469  0.008163  0.542857
ENTJ       0.043478  0.260870  0.173913  0.217391  0.130435  0.173913       NaN
ENTP       0.137931  0.282132  0.018809  0.379310       NaN  0.050157  0.131661
ESFJ       0.485714  0.271429  0.028571       NaN       NaN       NaN  0.214286
ESFP       0.685185  0.037037  0.018519  0.092593       NaN  0.148148  0.018519
ESTJ       0.057592  0.136126  0.109948  0.036649  0.157068  0.015707  0.486911
ESTP       0.047619  0.380952  0.063492  0.031746       NaN       NaN  0.476190
INFJ       0.027586  0.700000  0.037931  0.024138  0.013793  0.103448  0.093103
INFP       0.076471  0.435294  0.052941  0.076471  0.017647  0.005882  0.335294
INTJ       0.146667  0.826667       NaN       NaN  0.026667       NaN       NaN
INTP            NaN  0.653846       NaN       NaN  0.038462       NaN  0.307692
ISFJ            NaN  0.016484  0.013736  0.043956       NaN  0.052198  0.873626
ISFP       0.083333  0.194444  0.111111       NaN       NaN  0.333333  0.277778
ISTJ       0.270085  0.273504  0.041026       NaN  0.001709       NaN  0.413675
ISTP       0.111607  0.035714  0.258929  0.044643  0.008929  0.107143  0.433036
```

```
Classification Report for Emotions:
              precision    recall  f1-score   support

       anger       0.18      0.37      0.24       528
     disgust       0.04      0.04      0.04       534
        fear       0.14      0.15      0.15       541
         joy       0.06      0.02      0.03       548
     neutral       0.26      0.28      0.27       518
     sadness       0.08      0.04      0.05       538
    surprise       0.16      0.17      0.16       519

    accuracy                           0.15      3726
   macro avg       0.13      0.15      0.14      3726
weighted avg       0.13      0.15      0.13      3726


Classification Report for Emojis:
              precision    recall  f1-score   support

           😊       0.29      0.33      0.31       548
           🤢       0.40      0.68      0.50       518
           😡       0.12      0.08      0.10       528
           😢       0.02      0.01      0.01       538
           😱       0.18      0.04      0.06       541
           😲       0.20      0.06      0.09       519
        🤷♂       0.09      0.24      0.14       534

    accuracy                           0.20      3726
   macro avg       0.19      0.21      0.17      3726
weighted avg       0.18      0.20      0.17      3726
```



- **DEBERTA**

	precision	recall	f1-score	support
ENFJ	0.00	0.00	0.00	84
ENFP	0.00	0.00	0.00	247
ENTJ	0.00	0.00	0.00	114
ENTP	0.00	0.00	0.00	300
ESFJ	0.00	0.00	0.00	19
ESFP	0.00	0.00	0.00	25
ESTJ	0.00	0.00	0.00	15
ESTP	0.00	0.00	0.00	36
INFJ	0.00	0.00	0.00	616
INFP	0.00	0.00	0.00	733
INTJ	0.00	0.00	0.00	500
INTP	0.00	0.00	0.00	643
ISFJ	0.00	0.00	0.00	74
ISFP	0.03	1.00	0.06	108
ISTJ	0.00	0.00	0.00	82
ISTP	0.00	0.00	0.00	130
accuracy			0.03	3726
macro avg	0.00	0.06	0.00	3726
weighted avg	0.00	0.03	0.00	3726

	precision	recall	f1-score	support
😊	0.00	0.00	0.00	548
😐	0.14	0.84	0.23	518
😡	0.10	0.04	0.06	528
😢	0.00	0.00	0.00	538
😱	0.00	0.00	0.00	541
😮	0.14	0.08	0.11	519
🤷‍♂️	0.00	0.00	0.00	534
accuracy			0.13	3726
macro avg	0.05	0.14	0.06	3726
weighted avg	0.05	0.13	0.06	3726

	precision	recall	f1-score	support
anger	0.00	0.00	0.00	528
disgust	0.00	0.00	0.00	534
fear	0.00	0.00	0.00	541
joy	0.00	0.00	0.00	548
neutral	0.14	0.96	0.24	518
sadness	0.00	0.00	0.00	538
surprise	0.12	0.03	0.04	519
accuracy			0.14	3726
macro avg	0.04	0.14	0.04	3726
weighted avg	0.04	0.14	0.04	3726

```
Analyzing relationships between MBTI types and predictions...

Top predicted emotions associated with each MBTI type:
pred_emotion   neutral  surprise
pred_type
ESTJ          1.000000       NaN
ESTP               NaN  1.000000
ISFJ          1.000000       NaN
ISFP          0.972087  0.027913

Top predicted emojis associated with each MBTI type:
pred_emoji          😐         😡         😲
pred_type
ESTJ        1.000000       NaN       NaN
ESTP             NaN  1.000000       NaN
ISFJ        1.000000       NaN       NaN
ISFP        0.857182  0.061518  0.081301
```

- **DISTILLGPT2**

	precision	recall	f1-score	support
😊	0.00	0.00	0.00	548
😐	0.14	1.00	0.24	518
😡	0.00	0.00	0.00	528
😟	0.00	0.00	0.00	538
😱	0.00	0.00	0.00	541
😲	0.00	0.00	0.00	519
🤷‍♂️	0.00	0.00	0.00	534
accuracy			0.14	3726
macro avg	0.02	0.14	0.03	3726
weighted avg	0.02	0.14	0.03	3726

	precision	recall	f1-score	support
anger	0.00	0.00	0.00	528
disgust	0.00	0.00	0.00	534
fear	0.00	0.00	0.00	541
joy	0.00	0.00	0.00	548
neutral	0.14	1.00	0.24	518
sadness	0.00	0.00	0.00	538
surprise	0.00	0.00	0.00	519
accuracy			0.14	3726
macro avg	0.02	0.14	0.03	3726
weighted avg	0.02	0.14	0.03	3726

```
              precision    recall  f1-score   support

        ENFJ       0.00      0.00      0.00        84
        ENFP       0.00      0.00      0.00       247
        ENTJ       0.00      0.00      0.00       114
        ENTP       0.00      0.00      0.00       300
        ESFJ       0.00      0.79      0.01        19
        ESFP       0.00      0.00      0.00        25
        ESTJ       0.00      0.00      0.00        15
        ESTP       0.00      0.00      0.00        36
        INFJ       0.00      0.00      0.00       616
        INFP       0.23      0.01      0.02       733
        INTJ       0.14      0.14      0.14       500
        INTP       0.20      0.02      0.04       643
        ISFJ       0.00      0.00      0.00        74
        ISFP       0.00      0.00      0.00       108
        ISTJ       0.00      0.00      0.00        82
        ISTP       0.00      0.00      0.00       130

    accuracy                           0.03      3726
   macro avg       0.04      0.06      0.01      3726
weighted avg       0.10      0.03      0.03      3726

Top predicted emotions associated with each MBTI type:
pred_emotion   neutral  surprise
pred_type
ENFP          1.000000  0.000000
ENTP          1.000000  0.000000
ESFJ          1.000000  0.000000
INFP          1.000000  0.000000
INTJ          1.000000  0.000000
INTP          1.000000  0.000000
ISFJ          0.727273  0.272727
ISTJ          0.800000  0.200000

Top predicted emojis associated with each MBTI type:
pred_emoji          😐     😡          😲
pred_type
ENFP        1.000000  0.0  0.000000
ENTP        1.000000  0.0  0.000000
ESFJ        1.000000  0.0  0.000000
INFP        1.000000  0.0  0.000000
INTJ        1.000000  0.0  0.000000
INTP        1.000000  0.0  0.000000
ISFJ        0.727273  0.0  0.272727
ISTJ        0.800000  0.2  0.000000
```

PERSONALITY TYPE	EMOJI
ENFJ	😡
ENFP	😢 , 😲
ENTJ	😊
ENTP	😲
ESFJ	😡
ESFP	😲
ESTJ	🤷‍♂️
ESTP	😊

PERSONALITY TYPE	EMOJI
INFJ	😢
INFP	😨
INTJ	😲
INTP	🤷‍♂️
ISFJ	😡
ISFP	😨
ISTJ	😐
ISTP	😡

Figure showing which personality type is more inclined to which emotion typ.

REFERENCES

- BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

- Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. Retrieved from https://arxiv.org/abs/1810.04805
- BERT (Bidirectional Encoder Representations from Transformers) revolutionized natural language understanding by pre-training transformers on a large corpus and fine-tuning them on downstream tasks, achieving state-of-the-art results across various NLP benchmarks. In this project, we leveraged BERT's powerful language modeling capabilities to predict personality types from text.

- RoBERTa: A Robustly Optimized BERT Pretraining Approach

- Liu, Y., Ott, M., Goyal, N., Du, J., & Reimers, N. (2019). RoBERTa: A robustly optimized BERT pretraining approach. Retrieved from https://arxiv.org/abs/1907.11692
- RoBERTa is an optimized version of BERT, which modifies the original pretraining strategy by removing the Next Sentence Prediction objective and increasing the training duration and data size. The improved performance of RoBERTa makes it a suitable model for tasks involving complex language understanding, such as personality prediction.

- DeBERTa: Decoding-enhanced BERT with Disentangled Attention

- He, P., Liu, X., & Gao, J. (2020). DeBERTa: Decoding-enhanced BERT with disentangled attention. Retrieved from https://arxiv.org/abs/2006.03654
- DeBERTa introduces innovations in BERT’s architecture by using disentangled attention and enhanced decoding strategies, resulting in improved language understanding, especially in complex NLP tasks. The model’s ability to handle finer nuances in text semantics is valuable for accurate personality prediction.

- DistilGPT-2: A Distilled Version of GPT-2

- Sanh, V., Debut, L., & Chaumond, J. (2019). DistilGPT-2: A distilled version of GPT-2. Retrieved from https://huggingface.co/DistilGPT2
- DistilGPT-2 is a smaller and faster variant of GPT-2, retaining most of its generative language capabilities while being less resource-intensive. Although not directly used for MBTI prediction, this model can generate diverse and engaging responses, which could complement a personality detection system by offering chatbot interactions.
- Transformers: State-of-the-art Natural Language Processing
- Wolf, T., Debut, L., Sanh, V., & others. (2020). Transformers: State-of-the-art Natural Language Processing. Retrieved from https://huggingface.co/transformers
- Hugging Face's Transformers library offers easy access to a wide range of pre-trained models, including BERT, RoBERTa, DeBERTa, and GPT-2. The library simplifies the process of fine-tuning and deploying transformer models, making it an essential tool in this project for model implementation and experimentation.
- Scikit-learn: Machine Learning in Python
- Pedregosa, F., Varoquaux, G., Gramfort, A., & others. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825-2830.
- Scikit-learn is a powerful Python library for machine learning, used in this project for tasks such as preprocessing, label encoding, and performance evaluation. Its simple and consistent API enables easy integration with deep learning workflows for handling nondeep learning tasks.
- PyTorch: An Imperative Style, High-Performance Deep Learning Library
- Paszke, A., Gross, S., & others. (2019). PyTorch: An imperative style, high-performance deep learning library. Retrieved from https://pytorch.org
- PyTorch is the deep learning framework used for training and implementing the BERTbased model in this project. Known for its flexibility, dynamic computation graph, and strong community support, PyTorch allows for easy experimentation and rapid prototyping of deep learning models.
- MBTI Personality Test Data: Dataset Source
- The MBTI dataset used in this project is sourced from the publicly available MBTI with Emotions and Emojis dataset, curated from various social media and online platforms. This dataset contains user-generated posts, which are labeled with corresponding MBTI personality types, emotions, and appropriate emoji suggestions. The dataset is available at https://www.kaggle.com/datasets/sbhatti/mbti-type.
- Hugging Face Model Hub
- Hugging Face Model Hub. (2021). Retrieved from https://huggingface.co/models
- The Hugging Face Model Hub is a repository that provides access to numerous pretrained transformer models, including BERT, RoBERTa, and DistilGPT2. It enables seamless fine-tuning and deployment of NLP models, playing a critical role in this project by providing easy access to pretrained models for the MBTI classification task.

- Kaggle: A Platform for Data Science Competitions

- Kaggle.com. (2021). Retrieved from https://www.kaggle.com
- Kaggle is a platform for data science competitions and datasets. It serves as a valuable resource for datasets used in various machine learning projects. The MBTI dataset used in this project was sourced from Kaggle, which contains both the raw and cleaned versions of the data.

- TQDM: Fast, Extensible Progress Bar
- TQDM is a Python library used in this project to show progress bars during the tokenization process and data handling. It provides a simple, efficient way to monitor the progress of loops and processes.

- TensorFlow: A Comprehensive Open-Source Machine Learning Library

- Abadi, M., Barham, P., Chen, J., & others. (2015). TensorFlow: A system for large-scale machine learning. Retrieved from https://www.tensorflow.org
- While PyTorch was used in the project, TensorFlow serves as an alternative deep learning framework. Its ecosystem is vast, and it's widely used for deploying models in production environments.

- Seaborn: Statistical Data Visualization

- Waskom, M., Botvinnik, O., & others. (2020). Seaborn: Statistical data visualization. Retrieved from https://seaborn.pydata.org
- Seaborn is a Python library used for data visualization. It complements Matplotlib, providing easier methods for creating statistically-informed plots, which were crucial in visualizing the performance of the models in the project.

- Matplotlib: Plotting and Data Visualization in Python

- Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in Science & Engineering, 9(3), 90-95.
- Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. In this project, it was used to generate charts and plots that depict model performance and data distributions, making the results more interpretable.