Enhancing MBTI Prediction and Sentiment Analysis with Advanced Language Models

1st Kavya Gundla
dept. Information Science
University of North Texas
Denton, USA
kavyagundla@my.unt.edu

2nd Parithosh Yadavathi Girish
dept. Information Science
University of North Texas
Denton, USA
parithoshgirish@my.unt.edu

3rd Pavan Kumar Behara
dept. Information Science
University of North Texas
Denton, USA
pavankumarbehara@my.unt.edu

4th Sai Teja Munja
dept. Information Science
University of North Texas
Denton, USA
saitejamunja@my.unt.edu

***Abstract*—A personality is a unique combination of traits that influences how someone thinks, feels, and behaves. The Myers-Briggs Type Indicator (MBTI) is a popular personality assessment tool used by people to check their personality, this categorizes humans into one of 16 personality types based on their preferences in four dimensions: Extraversion (E) - Introversion (I), Sensing (S) - Intuition (N), Thinking (T) - Feeling (F), and Judging (J) - Perceiving (P).For example, a person who is introverted, sensing, feeling and perceiving would be identified as ISFP. In this project, we explored the application of transformer-based models to predict MBTI personality types based on textual data (forum posts). In order to achieve this, we used state-of-the-art NLP models such as BERT, RoBERTa, DistilBERT, XLNet, and GPT-2 to extract meaningful features from text data and build predictive models. By fine-tuning these models on MBTI dataset, we developed accurate classifiers capable of predicting an individual's MBTI type based on their posts. Additionally, we conducted many trail errors to finalize the hyperparameters so as to improvise the predictive performance of our models. The models are evaluated in terms of accuracy, f1-score, confusion matrix and also by testing with user input. XLNet and GPT-2 performed well in predicting the personality types with an accuracy of 68 and rest of the models also achieved accuracy around 66. Furthermore, confusion matrix of each personality type and their corresponding 4 labels are conducted for deeper analysis. The insights gained from this project not only contribute to the advancement of NLP research but also provide valuable applications in various domains such as personalized marketing, social media analysis and psychology.**

***Index Terms*—MBTI, Transformer-based Models, NLP, Hugging Face, BERT, RoBERTa, DistilBERT, XLNet, GPT-2, Sequence Classification, Psychology**

I. Introduction

In today's digital era, understanding personality has become increasingly important, with online interactions being the most part of our personal and professional lives. Studying written content, like what people post on social media or forums, is a great way to understand how they think and behave. The Myers-Briggs Type Indicator (MBTI) is a popular tool that sorts people into different personality types based on how they see the world and make decisions. Knowing someone's personality type can be really useful in fields like Human Resources, psychology, marketing, and customizing experiences. [15] The MBTI categorizes people into 16 types based on four main preferences:

- **Introversion (I) or Extroversion (E):** examines where people get their energy from and how they interact with the world around them. Extroverts are like social butterflies who get motivated on being around other people and engaging in external activities. They often feel energized and motivated when they're surrounded by others and enjoy participating in social events and group activities. On the other case, Introverts are like deep thinkers who prefer spending time alone or with a small, close group of friends. They often feel drained by too much social interaction and need time alone to recharge their batteries. Introverts tend to be reflective, finding fulfillment in their inner thoughts and ideas.
- **Intuition(N) or Sensing(S):** This looks at how people gather and understand information. Sensors are like detectives who pay close attention to what's happening around them right now. They depend on their five senses to pick up deeper details and focus on what's happening in the present moment. On the other hand, Intuitive are like visionary people who are more interested in the big picture and future possibilities. They often think about creative ideas and trust their gut feelings to guide them.
- **Thinking(T) or Feeling(F):** This part explores how individuals make decisions. Thinkers are like scientists who use logic and reason to analyze situations objectively. They prioritize facts and evidence over emotions when making choices. Feelers, on the other hand, are like artists who make decisions based on their personal values and the impact on others. They're more in tune with their emotions and consider how their decisions will affect people's feelings.
- **Judging(J) or Perceiving(P):** This shows how people organize their lives and approach tasks. Judgers are like planners who prefer structure and organization. They like to have things settled and decided, and they feel more comfortable when there's a clear plan in place. Perceivers, on the other hand, are like explorers who enjoy flexibility . They're adaptable and open to new experiences, preferring to go with the flow rather than stick to a strict schedule.

MBTI plays an important role in healthcare, especially in psychology. It provides a framework for understanding different personality types based on preferences in how individuals see the world and make decisions. This understanding can be helpful in different areas of psychology, including personality psychology and counseling. Psychologists often use MBTI as a tool for assessing an individual's personality type. By understanding a person's MBTI type, psychologists can gain insights into their strengths, weaknesses, and preferences, which can inform therapeutic interventions and personal development strategies. MBTI is commonly used in career counseling to help individuals identify suitable career paths based on their personality preferences. [15] By matching personality types with specific job roles and work environments, psychologists can assist clients in making informed career decisions that align with their natural inclinations and strengths. It is also valuable in resolving conflicts and improving interpersonal relationships. By recognizing and appreciating the differences in personality types, psychologists can help individuals and groups resolve conflicts more effectively and improve greater understanding among them. The foundational "Attention is all you need" [17] introduces us the Transformer architecture. While not directly focused on text classification, it provides the groundwork for the application of transformers in various NLP tasks, including sentiment analysis and topic modeling, which are essentially text classification problems. Transformer models, including BERT, RoBERTa, DistilBERT and others like GPT (Generative Pre-trained Transformer) and XLNet, have improved natural language processing tasks due to their ability to handle long-range text and capture contextual information effectively. Transformer models are based on the transformer architecture, which consists of an encoder-decoder structure with self-attention mechanisms. This architecture allows the model to process input sequences in parallel, making it highly efficient. BERT is a transformer-based model introduced by Google in 2018 and it is pre-trained on large-scale data using masked language modeling and next sentence prediction tasks. [16] BERT stands for Bidirectional Encoder Representation from Transformers, has been shown to achieve state-of-the-art performance on various natural language understanding tasks, including text classification, sentiment analysis, and question answering. Roberta is a robustly optimized approach of bert with an additional classifier on top of it for effective performance and distilbert is a smaller and faster version of bert specifically designed to process medium level datasets for faster training. XLNet, also developed by Google, combines ideas from autoregressive models like GPT and autoencoding models like BERT. It uses permutations of input sequences during pre-training so as to capture bidirectional context without compromising on the autoregressive property. XLNet has shown improvements over BERT on various benchmark tasks or datasets. GPT (Generative Pre-trained Transformer) is another transformer-based model introduced by OpenAI, primarily focused on generative tasks. GPT is unidirectional and autoregressive which means it generates text one token at a time from left to right. GPT has been mainly used for tasks such as text generation, language translation, and dialogue generation. However, GPT2 which is a decoder-only transformer, the last token of the input sequence is used to make predictions about the next token that should follow the input (This means that the last token of the input sequence contains all the information needed in the prediction), we can use that information to make a prediction in a classification task instead of generation task.

Problem Statement: Previous studies have focused on using traditional machine learning methods to predict MBTI personality types. However, in our project, we conducted whether advanced language models like BERT, XLNet, GPT, RoBERTa, and DistilBERT can effectively predict MBTI personality types and classify the human text or social media posts. Furthermore, evaluated the performance of these models against user input for deeper analysis.

II. Literature Review

Pan and Zeng (2023) explored deeper into the inquiry of whether Large Language Models (LLMs) display different personalities and analyzed for the utilization of the MBTI test as a metric for evaluating LLMs' personality traits. Their investigation significantly contributed to extracting the hidden tendencies of LLMs and their potential to show human-like personalities. La Cava, Costa, and Tagarelli (2024) extensively examined the capacities of open Large Language Models (LLMs) in showing human personalities, while also raising ethical concerns surrounding the deployment of such models. Their scholarly inquiry provided the required need for analyyzing the improvements of LLMs' capacity to evaluate human traits. Vásquez and Ochoa-Luna (2021) conducted a study on transformer-based methodologies for personality detection using the Myers-Briggs Type Indicator (MBTI) model. Their research involved evaluating the performance of transformer-based models in accurately predicting personality types from textual data, therefore contributing significantly to the advancement of Natural Language Processing (NLP) techniques for personality prediction. Johnson and Murty (2023) provided a machine-learning strategy aimed at augmenting data connectivity in text-based personality prediction by evaluating the mapping of different data sources. Their research primarily concentrated on enhancing the accuracy and precision of personality prediction models through the combination of different unstructured datasets. Perera and Costa (2023) showed a deeper review of techniques for personality classification using both machine learning and deep learning methodologies. Their comprehensive survey combined research discoveries and methodologies for personality detection from textual data, providing better insights into cutting-edge approaches in the transformers field.Tareaf (2022) explored the use of Reddit to predict personality types from textual input using MBTI, used a large dataset of Reddit users and different machine learning models to create a prediction. BERT model was used.Features are selected and reduced to extract only the necessary language contents for some models like XGBoost and SVM and TF-IDF is used for calculating and extract features.Wu et al. (2023) proposed a method using BERT to address text understanding issues in natural language processing (NLP). The proposed BERT text labels classification model is highly flexible and can be fine-tuned to specific domains or applications by training it on custom datasets. Its core advantage is its ability to handle long sequences of text data, which can be challenging for other classification algorithms.Elmoushy et al. (2023) discussed the problem of predicting personality traits from online activity by the informal style of online communication , they provided a new technique that involves a two-step procedure where in text input is first condensed using a transformer-based summarization model, and then personality is classified using the DistilBERT model. These techniques enabled the research to categorize MBTI types with high accuracy, indicating that more research and optimization of these approaches may be necessary for a range of NLP applications. Jayaraman et al. (2023) provided a different approach that uses the XL-Net model—a permutation language model that successfully captures bidirectional context—to predict personality traits from textual input. It talks about how text inputs from social media and other textual sources are used to train XLNet to detect personality types based on the MBTI and the Big Five model. This showed how well deep learning techniques can be applied to the challenging problem of psychological profiling, while also improving the accuracy of personality evaluations and expanding the potential uses of NLP in psychology. Darapaneni et al. (2023) discussed utilizations of the BERT and GPT-2 models for the abstractive text summarization, especially on COVID-19 dataset. They implemented BERT for an extractive summarization, and GPT-2 for the abstractive one and they improved through regulation techniques. This was meant to enhance the globular similarity in the generated summaries. The models were evaluated with Rouge and Bleu scores which needed to assess summarization qualities. Joshy and Sundar (2022) evaluated the performances of BERT, DistilBERT, and RoBERTa for sentimental analysis on movie reviews and tweets relevant to COVID-19. They found that BERT has outdone the other two models in terms of accuracy. It highlights the effectiveness of applying advanced NLP techniques for sentiment analysis, showing BERT's superior capability in handling such tasks.

III. Objectives of the Study

This project aims to enhance mbti personality prediction using language models, so the main objectives of this research are:

- To compare the performance of transformer-based models; BERT, RoBERTa, DistilBERT, XLNet and GPT-2 for classifying the human written data and predicting MBTI personality types based on the posts.
- To evaluate the trained transformer-based models for personality prediction using evaluation metrics like confusion matrix, accuracy, precision etc.
- To compare each personality type accuracy obtained by the models.
- To test the models against user text input so as to find out the predicted MBTI personality type.

IV. Data Collection

The MBTI dataset is collected from the Kaggle, the data in it is collected from a personality café forum which provided personality type and written posts of wide range of people. The dataset is a csv file. The main purpose behind this dataset is that it can be used for machine learning tasks to predicting the personality types and also to determine individuals type based on the text they have written in the posts. Dataset link : MBTI

V. Exploratory data analysis (EDA) and Hypotheses for the Study

This section discusses the dataset; data distribution and information so that the insights can be used for further analysis such as data transformation and modeling. Exploratory data analysis involves examining data sets to understand their main characteristics, often using visual methods like charts and graphs. It helps in detecting patterns, outliers, and relationships within the MBTI , providing insights for further analysis. EDA can reveal important information about the distribution of personality types, potential errors, and the need for data preprocessing. We explored to find clues about what's hidden within the data before diving deeper into analysis. EDA is crucial as it lays the foundation for making informed decisions and formulating hypotheses about our research. We have used python libraries; pandas, numpy for handling the data. Additionally, the natural language toolkit's stopwords are used and for visualization we used matplotlib library. The MBTI dataset has 8675 rows and 2 columns; types and posts. Types contains the users mbti personality type and posts consists of users recent 50 posts and they are separated by 3-pipe character. The count of each personality type is shown below:

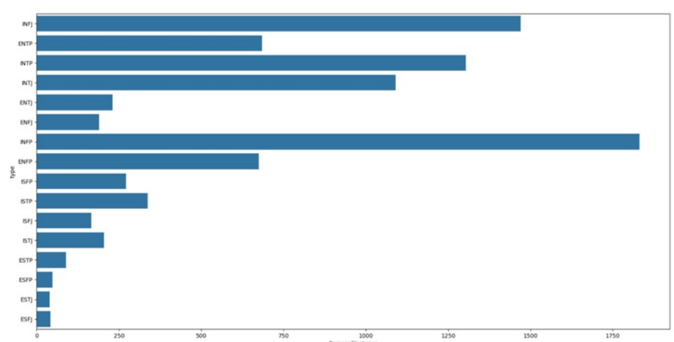

Fig. 1. Distribution of MBTI types

The most common personality type in the data is INFP, with 1832 users, followed by INFJ, with 1470 users, and the least common is ESTJ, with only 39 users. The dataset includes 16 different MBTI personality types. The posts consist of both text and some links. We also examined the frequency of stop words to identify the most commonly repeated words in the posts 2

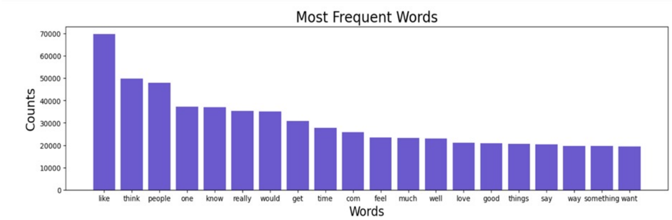

Fig. 2. Most Frequent Words

Furthermore, the posts are analyzed to see what are the data cleaning steps that needs to be done for efficient performance. We found out there are unnecessary links, symbols and characters that can be removed from the posts.

VI. Data Analytics

This section discusses data cleaning steps that are conducted and how the data is prepared for transformer-based models, various hyper parameters and strategies that are set for text classification. We performed data cleaning to prepare the data for model training using transformed based models. There are no missing values in the dataset. After analyzing the posts and the words, first the text is converted to lowercase for uniformity and then the non-alphabetic characters, symbols and URLs or links are removed for better analysis. By using nltk, stop words such as 'and', 'is' are removed for dimensionality reduction. The mbti types are label encoded into 0 to 15 in order for our model to understand the data, this means that there are 16 classes for the models to classify the text.

A. Models Implementation

We chose these transformer models for their diverse capability and suitability for text classification tasks. BERT is a Bidirectional Encoder Representation from Transformers; it has an encoder-decoder kind of architecture but here we focus mainly on encoder part as we are doing a text classification here. All the models take tokens as inputs. BERT is capable of capturing contextual information from both directions of the input text. It's widely used for various natural language processing tasks, including text classification. RoBERTa is built upon the BERT architecture with additional pre-training objectives and optimizations. DistilBERT is a distilled version of the BERT model, designed to be smaller and faster while retaining much of the performance. XLNet is based on permutation-based pre-training objectives to extract bidirectional context information more effectively. It is designed to address some limitations of BERT's masked language modeling objective.

TABLE I
Fine-tuning parameters-1

Hyperparameters	Values
Max length	512
Epochs	12
Batch Size	8
Learning Rate	2e-5

The dataset is split into 80 training data and 20 testing data for all the models to ensure a fair comparison. We prepared the input data using PyTorch and we implemented all these in a GPU environment for faster training. For all the models, a specific variant for classification tasks called ForSequence-Classification is used. After many trails and errors, the hyper-parameters are set for BERT, RoBERTa, DistilBERT. Adamw optimizer was used for all the models. The text is tokenized using the respective tokenizer for all the models, for example, for bert model we used bert tokenizer. A method encodeplus was used for tokenization and this tokenizer arranges the tokens based on the fixed sequence length. The input ids and attention masks are stored for further analysis. Additionally, input tensors are prepared along with the data loaders are created for efficient training and testing. The training process for BERT took 2hr 15mins, for Roberta it was 2hr 6mins and 1 hr 11 mins for distilbert.

For XLNet and GPT-2, the fine-tuning hyper parameters II are same except for epochs because when we were conducting with different parameters, we got good performance with just 3 epochs so in order to prevent overfitting the epochs were set to 5. XLNet took 1hr 50mins to complete its training process while GPT-2 took 1 hr 7mins.

TABLE II
Fine-tuning parameters for XLNet and GPT-2

Hyperparameters	Values
Max length	512
Epochs	5
Batch Size	8
Learning Rate	2e-5

VII. Data Visualization and Results

This section shows the results obtained after training and evaluating all the models. We conducted evaluation for all the models with 20 percent testing data and then evaluated the performance of these models in the form of accuracy, classification report that includes precision, f1-score, recall and confusion matrix for personality types and also for each label for better analysis of the models. Additionally, we also tested our models against user input to find out if it correctly identifies or not.

XLNet appears to be the best-performing model across most personality types, closely followed by GPT-2. Even though GPT-2 achieved an overall accuracy with its faster training of 0.68, which is higher than XLNet's 0.67, it's notable that XLNet consistently performed well across all personality types. Additionally, as shown in 3 BERT, Roberta, and DistilBERT showed accuracies of 66.46, 65.99, and 66.05 respectively.

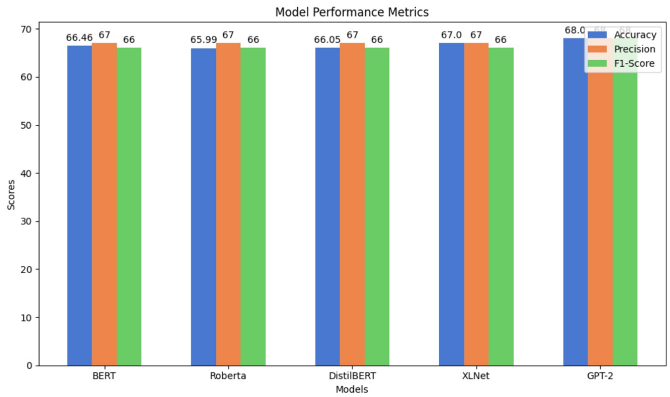

Fig. 3. Performance of the models

In the table III, we can observe that XLNet has the highest average accuracy across all personality types. This indicates that XLNet might be the most effective model for predicting MBTI personality types.

For INFJ, INTP, ISTP GPT2 has the highest accuracy. For ENTP, BERT and Roberta have the highest accuracy. For INTJ, INFP, ISFP XLNet has the highest accuracy. For ENTJ, ISTJ BERT has the highest accuracy. For ENFJ, Distilbert has the highest accuracy. For ENFP, Roberta has the highest accuracy.For ISFJ, ESTJ Roberta has the highest accuracy. For ESTP, Distilbert has the highest accuracy. ESFP is the least type with less rows in the dataset so GPT2 gave the highest accuracy. For ESFJ, Roberta and GPT2 both have the highest accuracy.

Among the models, XLNet seems to perform consistently well across various personality types, showing its model effectivity. BERT also shows competitive performance, performing well for several personality types. Roberta and GPT2 also demonstrate strong performance for specific personality types. Distilbert appears to perform moderately well but might not be the best choice for all personality types. XLNet and GPT2 have the highest accuracy for ESFP, indicating they might be better suited for this personality type.

Type	BERT	Roberta	Distilbert	XLNet	GPT2
INFJ	62.15	57.99	64.93	47.92	69.10
ENTP	70.37	71.11	64.44	59.26	63.70
INTP	72.01	74.40	72.01	72.35	78.84
INTJ	64.77	61.14	67.36	77.20	62.18
ENTJ	70.45	61.36	70.45	63.64	56.82
ENFJ	53.66	41.46	60.95	56.10	41.46
INFP	77.03	74.59	70.00	82.97	71.62
ENFP	61.60	69.60	64.80	67.20	68.80
ISFP	56.60	56.60	43.40	64.15	56.60
ISTP	55.22	64.18	65.67	56.72	68.66
ISFJ	46.67	62.22	55.56	62.22	57.78
ISTJ	56.82	56.82	56.82	50.00	63.64
ESTP	46.67	60.00	66.67	53.33	60.00
ESFP	25.00	0.00	25.00	0.00	12.54
ESTJ	42.86	57.14	42.86	28.57	57.14
ESFJ	42.86	0.00	42.86	42.86	42.86

TABLE III
ACCURACY OF THE MODELS FOR EACH PERSONALITY TYPE

INFP is the highest personality type in the dataset with a greater number of users, which means 21 percent of the data are INFP users. So, as there is no equal distribution among the personality types or classes, it is obvious that every model shows highest performance for INFP. To gain deeper insights, we further analyzed the confusion matrix for each model to understand true positives and other metrics.

As shown below 4in the confusion matrix for XLNet, we can observe that 307 instances of INFP are truly predicted as INFP which is the highest true positives then the second highest is the INTP with 212 instances out of 1735 testing data. 61 instances of INFJ are incorrectly predicted as INFP which is the highest true negatives values. INFJ, INFP, INTJ and INTP are the highest performing types among others.

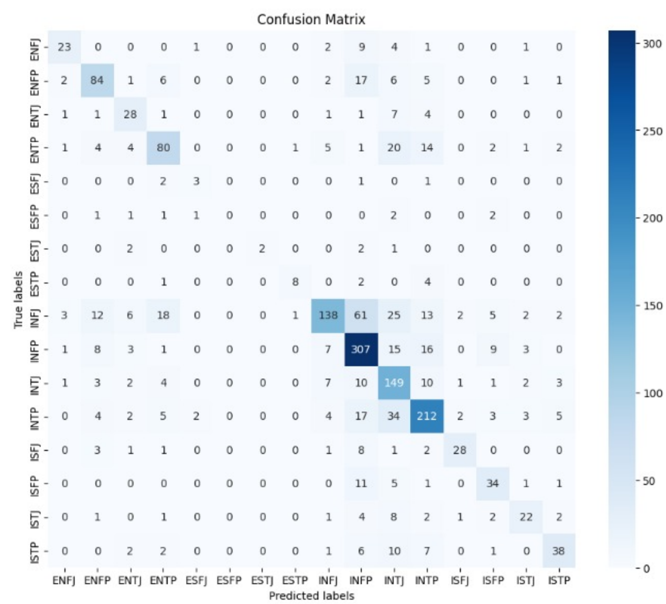

Fig. 4. XLNet's confusion matrix

The below image 5 shows the XLNet's 4- labels confusion matrix, 1266 instances of Introverted users are correctly predicted as introverts and then similarly in the case of intuition and others. The highest misclassification is with J as P with 192 instances and then next is P as J with 142 instances, it can be said that most of the misclassifications happened in this label. Similalrly, for other labels the misclassifications were in the case of J/P label.

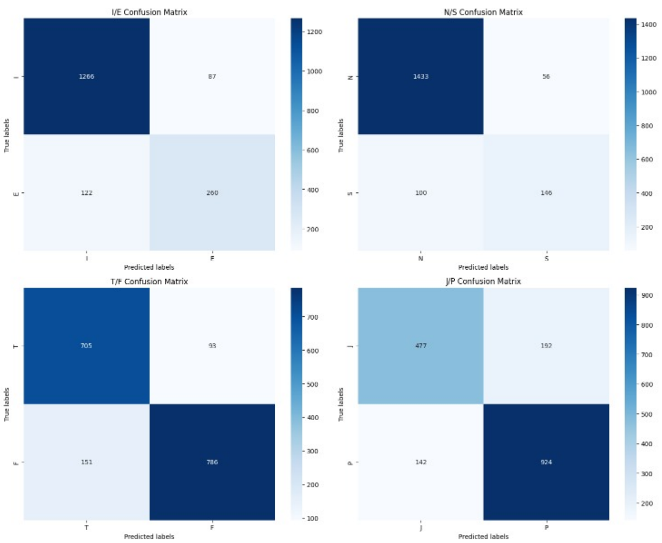

Fig. 5. Confusion matrix of XLNet's 4-labels

Furthermore, we tested the models against user input. We saved al the trained models by pushing them to the Hugging Face Hub and then loaded the pre-trained models for testing it with user input. Testing the mode with the user input is another way of evaluating the model performance. So, we have given a user input as you can see in the picture 6 , the input is given is in the form of tweets like how a person with INFP personality tweets. So, all the models except distilbert predicted correctly. Distilbert predicted as INFJ. There could be several reasons for this to happen, one of them is distilbert showed the lowest individual accuracy than other models in the case of INFP and also 41 instances of INFP were misclassified as INFJ with the testing data.

- Given input text: "Woke up this morning with a melody stuck in my head. Anyone else ever get song ideas in their dreams? musicmaker ,Just finished reading "The Little Prince." So beautifully simple, yet so profound. Makes you question everything. philosophy books ,Spending the afternoon sketching in the park. The sunlight filtering through the leaves is pure magic. naturephotography ,artist. . . . ."

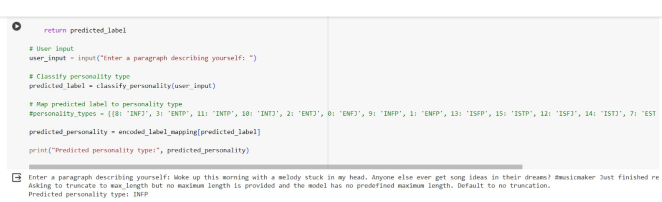

Fig. 6. Testing with user input

VIII. Conclusion

In conclusion, our research explored deeper into the application of transformer-based models for predicting individuals' personality types from human-generated text data. This involved a comprehensive process of collecting the data related to the Natural Language Processing (NLP) task of text classification, figuring out the optimal training objectives through many trails and erros, including hyperparameters and optimizations, and improving their efficiency. Through the utilization of various models such as BERT, RoBERTa, DistilBERT, GPT-2, and XLNet, we improved their performance in identifying patterns associated with diverse personalities. Notably, among these models, XLNet and GPT-2 showed better performance with consistently high accuracies across all personality types. This suggests their potential utility in tasks involving the classification of large human-written text. Therefore, our findings contribute many valuable insights that can be related to refining methodologies not only within psychology but also in the broader field of data science. This improvement, in turn, promises to advance our study of human behavior in the context of language models. Looking ahead, our future research aims to explore deeper into the field of text classification using transformer and language models, with particular focus on generative models. We want to undertake research in developing models similar to ChatGPT, having the capability to predict personality types based on prompts explaining the reason behind each predictde type, while also working as conversational chatbots. This dual functionality can be used for applications ranging from psychological tests to personalized conversational agents, thereby paving the way for novel advancements at the fusion of AI and human interaction.

References

[1] Pan, K., Zeng, Y. (2023). Do llms possess a personality? making the mbti test an amazing evaluation for large language models. *arXiv preprint arXiv:2307.16180.*

[2] La Cava, L., Costa, D., Tagarelli, A. (2024). Open Models, Closed Minds? On Agents Capabilities in Mimicking Human Personalities through Open Large Language Models. *arXiv preprint arXiv:2401.07115.*

[3] V´asquez, R. L., Ochoa-Luna, J. (2021, October). Transformer-based approaches for personality detection using the MBTI model. *In 2021 XLVII Latin American Computing Conference (CLEI)* (pp. 1-7). IEEE.

[4] Johnson, S. J., Murty, M. R. (2023). Machine Learning Approach to Improve Data Connectivity in Text-based Personality Prediction using Multiple Data Sources Mapping. *Journal of Scientific Industrial Research, 82* (1), 109-119.

[5] Perera, H., Costa, L. (2023). Personality Classification of text through Machine learning and Deep learning: A Review (2023). *Authorea Preprints*

[6] Elmoushy, S., Saeed, M., Gomaa, W. H. (2023, July). Empowering MBTI Personality Classification through Transformer-Based Summarization Model. In *2023 Intelligent Methods, Systems, and Applications (IMSA)* (pp. 26-31). IEEE.

[7] Jayaraman, A. K., Ananthakrishnan, G., Trueman, T. E., Cambria, E. (2023). Text-based personality prediction using XLNet. *Advances in Computers.*

[8] Tareaf, R. B. (2022, December). MBTI BERT: A Transformer-Based Machine Learning Approach Using MBTI Model For Textual Inputs. In *2022 IEEE 24th Int Conf on High Performance Computing Communications; 8th Int Conf on Data Science Systems; 20th Int Conf on Smart City; 8th Int Conf on Dependability in Sensor, Cloud Big Data Systems Application (HPCC/DSS/SmartCity/DependSys)* (pp. 2285-2292). IEEE.

[9] Wu, S., Huang, Z., Feng, H. (2023, August). Text Labels Classification Model based on BERT Algorithm. In *2023 4th International Conference on Big Data Artificial Intelligence Software Engineering (ICBASE)* (pp. 329-332). IEEE.

[10] Darapaneni, N., Prajeesh, R., Dutta, P., Pillai, V. K., Karak, A., Paduri, A. R. (2023, May). Abstractive Text Summarization Using BERT and GPT-2 Models. In *2023 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT)* (pp. 1-6). IEEE.

[11] Joshy, A., Sundar, S. (2022, December). Analyzing the performance of sentiment analysis using Bert, Distilbert, and Roberta. In *2022 IEEE International Power and Renewable Energy Conference (IPRECON)* (pp. 1-6). IEEE.

[12] Allibhai, J. (2022, July 18). Introduction to text classification using transformers. Medium.

[13] Cerkez, N., Vrdoljak, B., Skansi, S. (2021). A method for MBTI classification based on impact of class components. *IEEE access, 9,* 146550-146567.

[14] Choong, E. J., Varathan, K. D. (2021). Predicting judging-perceiving of Myers-Briggs Type Indicator (MBTI) in online social forum. *PeerJ, 9,* e11382.

[15] Ramachandran, V., Loya, A., Shah, K. P., Goyal, S., Hansoti, E. A., Caruso, A. C. (2020). Myers-briggs Type indicator in medical Education: a narrative review and analysis. *Health Professions Education, 6*(1), 31-46.

[16] Gillioz, A., Casas, J., Mugellini, E., Abou Khaled, O. (2020, September). Overview of the Transformer-based Models for NLP Tasks. In *2020 15th Conference on Computer Science and Information Systems (FedCSIS)* (pp. 179-183). IEEE.

[17] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Polosukhin, I. (2023). Attention is all you need. arXiv 2017. *arXiv preprint arXiv:1706.03762, 3762.*