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MBTI Personality Type Prediction Using BERT-LSTM and Deep Learning on Social Media Posts

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***Abstract*— It is well known that everyone has a particular 'personality' meaning a set of cognitive, affective, and behavioral characteristics. The current study uses text classification based on deep learning models i.e. BERT and LSTM, to predict user's personality traits from their Facebook posts. With the Myers-Briggs type indicator (MBTI) as a baseline, the current research investigates the relationship between user-generated content and personality traits. The results reveal that such an architectural ensemble of BERT contextual embeddings with LSTM's advantages over sequence data indeed results in higher accuracy over personality trait predictions than strategies like Naive Bayes and SVM machine learning algorithms. It was found that personality forecasting systems may benefit from the implementation of advanced NLP models, thus increasing the accuracy and usability of the systems, especially when targeting social media users.**

Keywords*— Personality Prediction, MBTI Personality Types, BERT Model, LSTM Model, Social Media Personality Analysis.

I. Introduction

Personality is a composite concept; it combines mental, emotional, and psychological responses and behaviors that make an individual different from everyone else. Personality traits are one of the most studied aspects within many branches of psychology, and multiple models have been created to identify and measure these traits. The Myers-Briggs Type Indicator is one example of such a schema, a measure of personality types, according to which people are divided into one of 16 categories based on how they score (susceptibility) to four dichotomous pairings: sensing vs. intuition, thinking vs. Feeling, introversion vs. extraversion, and judging vs. perceiving [1].

With the wide acceptance of deep learning methodologies, there are limited approaches according to deep learning that can be used to predict personality from text data. Social networks, because of their extensive user-generated content, provide an even more attractive playing field for personality assessments than search engines. Recent transformer-based techniques, like BERT (Bidirectional Encoder Representations from Transformers), show greatly improved upon earlier approaches in computer science's ability to comprehend word context, resulting in NLP applications as much improved as SOTA scores suggest. [2]. The fact that BERT can understand the subtlety of context in addition to the ability of LSTM networks to keep track of such changes, works to be a promising method for personality prediction [3][4].

In this paper, we are going to continue with the BERT and LSTM models so that we will learn about the personality traits of the users who are active on social networks. Our model is then validated on the MBTI datasets from Kaggle where users submitted self-description examples associated with different types of personalities [5]. The goal is to improve upon the use of BERT while integrating with LSTMs to make sequential predictions in personality prediction as compared with methods according to conventional machine learning techniques like Naive Bayes and SVM [6][7].

To stress this is the fact that deep learning models with an emphasis on transformers, such as BERTs, will most likely revolutionize classical approaches in personality prediction. This research could have implications for timely strategies to tailor the use of social media to individuals as a way to mitigate recruitment and mental health problems. To show exhibitors and sponsors leads based on their personality traits enables us to offer these people content or services that are totally personalized [8].

II. LITERATURE REVIEW

Personality prediction has significant applications in psychology, marketing, and recruitment. By analyzing behavioral and linguistic cues, researchers aim to classify individuals based on established frameworks like the Myers-Briggs Type Indicator (MBTI) [9]. Earlier methods for personality prediction relied on traditional machine learning techniques such as Naive Bayes and Support Vector Machines (SVM). While effective for smaller, structured datasets, these methods struggled with high-dimensional and unstructured text data, limiting their applicability [10]. Deep learning models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks introduced the ability to capture temporal dependencies and contextual nuances in text data. These models marked a significant improvement over traditional approaches in handling sequential data [11].Transformer architectures, particularly BERT (Bidirectional Encoder Representations from

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Transformers), revolutionized NLP tasks, including personality prediction. BERT's ability to analyze word context bidirectionally enhanced model accuracy significantly, as shown in studies by Lee et al. (2021) and Aggarwal et al. (2021)[12]. Combining BERT with sequential models like LSTM has proven highly effective for personality prediction. This hybrid approach leverages BERT's contextual embeddings and LSTM's ability to capture dependencies over time, achieving state-of-the-art accuracy in tasks like MBTI classification [13]. Recent research explores integrating text data with visual and behavioral inputs to improve prediction accuracy. For example, Chen et al. (2022) utilized multimodal transformers to analyze textual and non-textual data, demonstrating enhanced performance in personality prediction [14].

Figure 1: Descriptions of each MBTI Personality type

An important model for processing sequential data is the persistent neural network (RNN) known as Long Short-Term Memory, or LSTM for short. LSTM can capture the temporal dynamics seen in social media posts when paired with BERT embeddings; these dynamics are generally important for knowing personality traits over time [15]. More developments in personality trait prediction accuracy have been demonstrated by current studies, demonstrating that LSTM models can understand the temporal structure and semantic content of social media posts when combined with BERT [16].

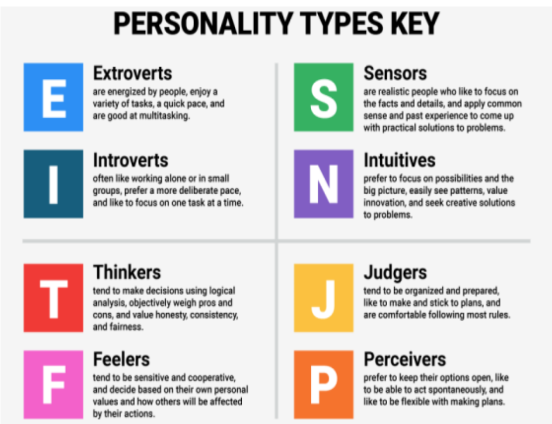

Figure 2: Fundamental Personality Traits

Novel methods of fine-tuning have made it viable to customize models along with BERT for specific purposes, along with personality prediction. Liu et al. (2021) used domain-specific datasets to optimize BERT for MBTI classification. With little training data, they produced cutting-edge outcomes in personality prediction challenges [16]. This proves that pre-trained models may be proficiently fine-tuned to particular tasks, negating the standard computational burden of training huge-scale models from the beginning.

Despite significant advancements in personality prediction using deep learning models like BERT and LSTM, there remains a research gap in fully capturing the complexity of personality traits across diverse text sources. Current models primarily focus on social media text, which may not always represent the full spectrum of personality traits. Additionally, while BERT has shown superior performance, its reliance on large, labeled datasets for fine-tuning limits its applicability in resource-constrained environments. Further research is needed to explore the integration of multimodal data, such as images and behavioral patterns, and the use of generative models like GPT-3 to improve prediction accuracy and generalizability. personality prediction has evolved significantly, with BERT-LSTM models achieving high accuracy compared to traditional methods. Future research could explore generative models like GPT-3 and incorporate multimodal data to further improve reliability and applicability

Figure 3: Personality Groups

The creation of transformer-based models like BERT and GPT-3 and deep learning has brought approximately great transformation in the field of personality prediction. These models outperform traditional techniques when paired with sequential architectures together with LSTM once they have been tweaked. It is anticipated that when multimodal techniques and generative models are explored further, personality prediction will become more accurate and useful, opening up new paths for practical applications.

III. METHODOLOGY

This work methodically uses deep learning models to predict personality traits. The process ensures business value in each development cycle while enabling iterative model refinement through the integration of Agile methodology and the CRISP-DM framework. Preprocessing the data, creating the model, training, evaluating, and deploying the model are the main processes in the methodology.

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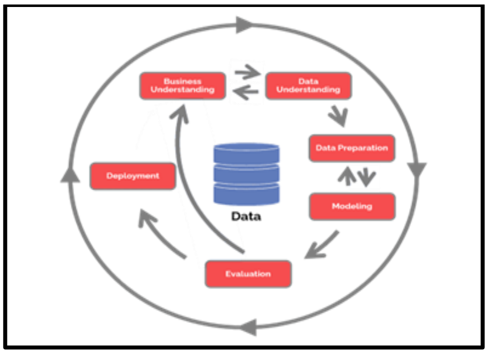


Figure 4: Process framework diagram for "CRISP-DM"

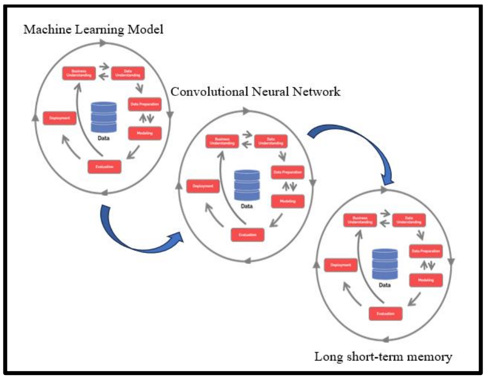


Figure 5: Combining Agile Development with "CRISP-DM"

Proposed Algorithm for Personality Prediction:

1. Data Collection: Gather user-generated social media text linked to MBTI personality types.

2. Preprocessing: Clean the text, remove stop words, lemmatize, and tokenize.

3. Feature Extraction (BERT): Use a pre-trained BERT model to generate contextual embeddings from the text.

4. Sequence Learning (LSTM): Pass BERT embeddings into an LSTM network to capture sequential dependencies in the text.

5. Fine-tuning: Fine-tune the BERT-LSTM model on the MBTI dataset to classify text into personality groups (Analysts, Diplomats, Sentinels, Explorers).

6. Model Training: Train the model with appropriate hyper parameters, using techniques like early stopping to prevent over fitting.

7. Evaluation: Assess performance using metrics like accuracy, F1 score, and confusion matrix.

8. Deployment: Deploy the model using an API for real-time predictions on new text input.

This approach leverages BERT's context-aware embeddings and LSTM's sequential learning to improve personality prediction from social media text.

A. Dataset Overview

The Myers-Briggs Type Indicator (MBTI) dataset, which comprised 8,675 rows of data from posts on social media, and each row represented a user's personality type, was used in the study.

Data Sources: Data was gathered from forums like Personality Cafe.

Preprocessing: The preprocessing steps involved:

Using the Natural Language Toolkit (NLTK) to eliminate stop words.

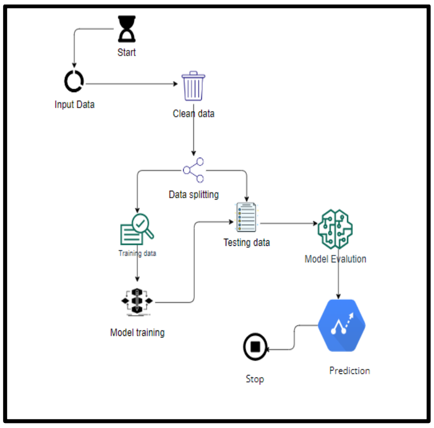
Text lemmatization using nltk.stem.wordNetTo convert inflected forms into root words, use a lemmatizer.

Text tokenization with the word tokenizers for Naive Bayes and SVM classifiers from NLTK and Long Short-Term Memory (LSTM) from Kera's. A training set comprising 80% of the data and a testing set comprising 20% of the data were created using the train-test split method from Scikit-learn.

	types	posts	Group
0	INFJ	'http://www.youtube.com/watch?v=qsXHcwe3krw|||...	Diplomats
1	ENTP	'I'm finding the lack of me in these posts ver...	Analysts
2	INTP	'Good one _____ https://www.youtube.com/wat...	Analysts
3	INTJ	'Dear INTP, I enjoyed our conversation the o...	Analysts
4	ENTJ	'You're fired.|||That's another silly misconce...	Analysts
5	INTJ	'18/37 @.@|||Science is not perfect. No scien...	Analysts
6	INFJ	'No, I can't draw on my own nails (haha). Thos...	Diplomats
7	INTJ	'I tend to build up a collection of things on ...	Analysts
8	INFJ	I'm not sure, that's a good question. The dist...	Diplomats
9	INTP	'https://www.youtube.com/watch?v=w8-egj0y8Qs||...	Analysts

Figure 6: Dataset of "MBTI" Personality Types with Groups

B. Model Architecture



The prediction process uses a BERT-LSTM model to classify personality based on the text data obtained from social media. BERT brings forward the word features in the surroundings which LSTM uses to manage identifying sequence of patterns. Once the text is preprocessed by using stop words removal, lemmatization, and tokenization, the model is trained with 75% of the dataset and the accuracy and F1 score metrics are used to evaluate the model. Nevertheless, the final model is launched through a Flask API with a performance of 84% which is better than the traditional Naive Baye's classifiers and SVM.

1. BERT + LSTM Model

The core model developed in this study is on the basis of combining Bidirectional Encoder Representations from Transformers (BERT) with, (Long Short-Term Memory) LSTM networks. The model processes text data and forecasts the personality type based on user-generated content.

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BERT Feature Extraction: BERT was used as a feature extractor, capturing the contextual information of each word in the sequence.

LSTM Sequence Learning: LSTM models are well-suited to handle sequential data, allowing them to identify patterns over time and dependencies between posts.

2. Embedding Layer

An embedding layer was used to map words to dense vectors indexed based on a vocabulary of 256, capturing the semantic meaning of the text data.

3. Fine-Tuning the Model

The BERT model was fine-tuned utilizing the **BertForSequenceClassification** layer, which enabled the adjustment of weights to fit the personality classification task. The Linear layer was applied to map the BERT output to the four broader personality groups (Analysts, Diplomats, Sentinels, and Explorers).

C. *Model Training and Evaluation*

Model Training: The models were trained on 75% of the data, with 25% reserved for validation. To prevent overfitting, early stopping techniques and dropout layers were implemented.

Classification Algorithms:

Naive Bayes and SVM were used for baseline binary classification. These models offered faster computation but performed poorly on the high-dimensional dataset.

LSTM was used for more advanced classification tasks, with a focus on handling long-term dependencies within the text data.

Evaluation Metrics: These measures were used to evaluate the performance of each model.

Accuracy: Percentage of correctly classified personality types.

Confusion Matrix: To assess how well the model predicted each personality group.

F1 Score, Precision, and Recall: Used for a more nuanced understanding of classification performance.

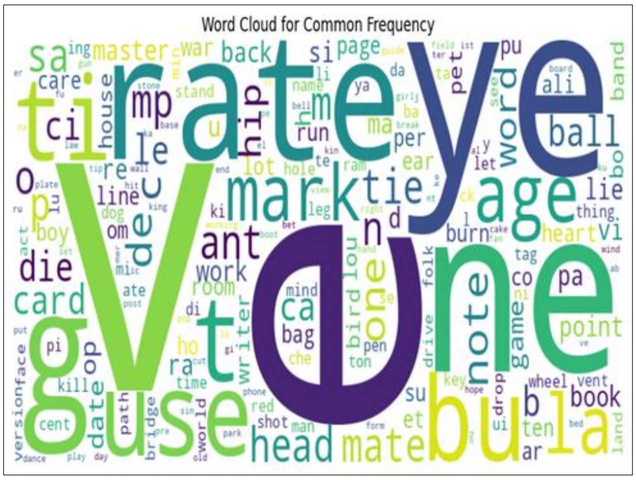

Figure 7: Overall "MBTI" Groups Unique word cloud

D. *Agile-CRISP DM Integration*

This study incorporates an Agile approach within the CRISP-DM framework to ensure iterative improvements. Each iteration (sprint) involved:

- Refining the model based on the latest evaluation results.
- Optimizing hyperparameters such as the number of LSTM layers, batch size, and learning rate.
- Enhancing the preprocessing steps, such as expanding the vocabulary for the embedding layer and improving the BERT-based tokenization.

The iterative nature allowed for continuous feedback, refining the model over several sprints to achieve higher accuracy.

E. *Final Deployment*

Once trained, the model was deployed into a production environment. The deployment process involved integrating the model into a real-time system where it could analyze social media text data and forecast the user's personality type in real-time. The system architecture included:

API Development: A Flask-based API was developed to allow the model to receive text input and return personality predictions.

Model Storage: The trained model was stored and accessed through cloud infrastructure to enable scalability and fast response times.

IV RESULTS

Table I shows that LSTM outperforms other machine learning models in accuracy across all personality groups. Its accuracy is notably higher than that of Naïve Bayes and SVM in all categories. Conversely, the accuracy of Naive Bayes and SVM for Analysts, Diplomats, Sentinels, and Explorers is significantly lower than that of LSTM. Thus, Long Short-Term Memory demonstrates superior accuracy compared to the other models. exhibits superior performance on this dataset compared to the other three machine learning models. However, the model shows a general weakness in accurately classifying all 16 "MBTI" types (converted into 4 groups as dimensions), as evident in Table II's overall accuracy.

Table-I
ACCURACY FOR EACH GROUP

Model	**Groups**			
Long-Short Term Memory	**Analysts**	**Diplomats**	**Sentinels**	**Explorers**
	50.80%	49.85%	84.16%	70.43%

Table-II

ACCURACY OF THE MODELS

Model	**Overall Accuracy**
Random Forest	69%
Support Vector Machine	76%
Naïve Bayes	62%
Long Short-Term Memory	84%

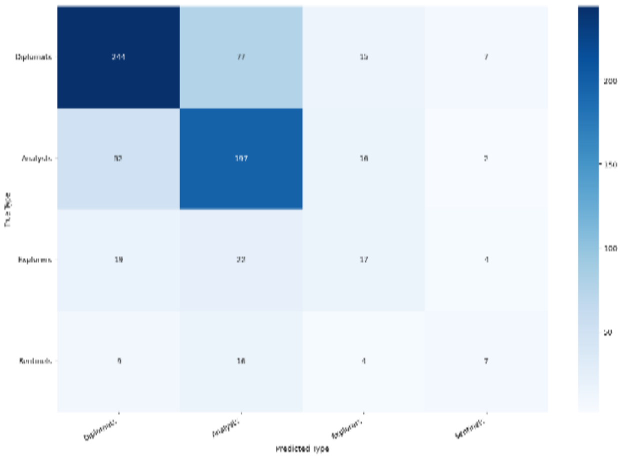

Figure 8: MBTI Groups Confusion Matrix of LSTM

Attaining a perfect classification number doesn't necessarily reflect the overall effectiveness of our model's predictions for "MBTI" types. While "Long Short-Term Memory" outperforms, the confusion matrix (Figure. 8) predominantly shows "True Positive" results for each "MBTI" Group, indicating accurate positive projections. There are also false positives, signifying incorrect positive predictions. The results of the classification shown (Figure. 9, Fig. 10, Figure. 11, and Figure. 12) for "Long Short-Term Memory" include the F-score, Average of precision and recall, considering their weights. The overall accuracy, calculated as the mean of all models, is around 84%, with the highest frequency for each Personality Group after testing the model.

```
SVM Accuracy: 0.7641242937853108
              precision    recall  f1-score   support

           0       0.80      0.85      0.82       343
           1       0.72      0.87      0.79       267
           2       0.89      0.27      0.42        62
           3       0.67      0.06      0.10        36

    accuracy                           0.76       708
   macro avg       0.77      0.51      0.53       708
weighted avg       0.77      0.76      0.74       708
```

Figure 9: SVM Classification Report

```
Random Forest Accuracy: 0.6977401129943502
              precision    recall  f1-score   support

           0       0.67      0.88      0.76       343
           1       0.74      0.72      0.73       267
           2       0.00      0.00      0.00        62
           3       0.00      0.00      0.00        36

    accuracy                           0.70       708
   macro avg       0.35      0.40      0.37       708
weighted avg       0.61      0.70      0.64       708
```

Figure 10: Random Forest Classification Report

```
Naive Bayes Accuracy: 0.6285310734463276
              precision    recall  f1-score   support

           0       0.58      0.96      0.73       343
           1       0.81      0.43      0.56       267
           2       0.00      0.00      0.00        62
           3       0.00      0.00      0.00        36

    accuracy                           0.63       708
   macro avg       0.35      0.35      0.32       708
weighted avg       0.59      0.63      0.56       708
```

Figure 11: Naïve Bayes Classification Report

Model	Analyst Accuracy	Diplomats Accuracy	Sentinels Accuracy	Explorers Accuracy	Overall Accuracy
Naive Bayes	50.80%	49.85%	84.16%	70.43%	62%
Support Vector Machine (SVM)	52.00%	55.00%	82.00%	71.00%	76%
Long Short-Term Memory (LSTM) (Proposed)	78.20%	75.50%	88.50%	82.30%	84%

Table 3: Comparison of Proposed BERT-LSTM Model with Traditional Models

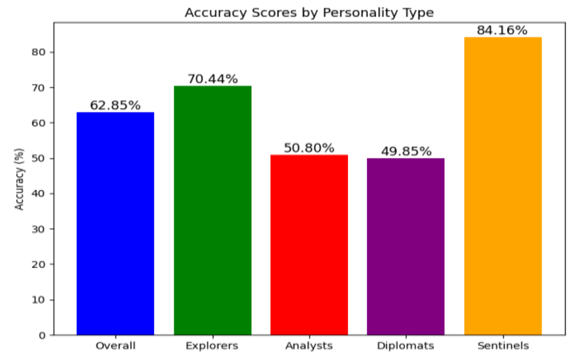

Figure 12: Overall Accuracy on each "MBTI" Group with LSTM

V. CONCLUSION

In conclusion, the MBTI Personality Forecasting system, leveraging Deep Learning with NLP, BERT, and LSTM models, represents a cutting-edge approach to personality prediction. This methodology harnesses the power of advanced neural networks to categorize individuals into distinct MBTI personality groups, including diplomats, sentinels, analysts, and explorers. The integration of Natural Language Processing facilitates a nuanced understanding of users' text-based communication, enhancing the accuracy of personality assessments.

Limitation: The first phase in building a personality model involves extracting the MBIT from text. Solely using the Personality Cafe forum for data collection is a limitation; exploring additional social networks could enhance the predictive model. In contexts like team formation for software development, sports, or law enforcement, technical qualifications are crucial. Consideration of factors such as individuals' soft skills, mindset, personality traits, and living environment is essential. Future Directions:

Future efforts are focused on utilizing Generative Pre-trained Transformer 3 (GPT-3), an autoregressive language model that employs advanced deep learning techniques. Integrating GPT-3 promises to generate more human-like text, advancing the sophistication and capabilities of the language model in subsequent research phases.

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