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Machine Learning Approach to Improve Data Connectivity in Text-based Personality Prediction using Multiple Data Sources Mapping

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This paper considers the task of personality prediction using social media text data. Personality datasets with conventional personality labels are few, and collecting them is challenging due to privacy concerns and the high expense of hiring expert psychologists to label them. Pertaining to a smaller number of labelled samples available, existing studies usually adds a sentiment, statistical NLP features to the text data to improve the accuracy of the personality detection model. To overcome these concerns, this research proposes a new methodology to generate a large amount of labelled data that can be used by deep learning algorithms. The model has three components: general data representation, data mapping and classification. The model applies Personality correlation descriptors to incorporate correlation information and further use this information in generating dataset mapping algorithm. Experimental results clearly demonstrate that the proposed method beats strong baselines across a variety of evaluation metrics. The results had the highest accuracy of 86.24% and 0.915 F1 measure score on the combined MBTI and Essays dataset. Moreover, the new dataset constructed contains 3,84,089 labelled samples on the combined dataset and can be further considered for personality prediction using the famous Five Factor Model thereby alleviating the problem of limited labelled samples for the purpose of personality detection.

Keywords: BERT, Deep learning, Natural language processing, Personality detection, Social media

Introduction

For humans, the usage of handwriting as a means of communication and expressing emotions is quite common. Analysis of human hand writing reveals its link to brain activity and psychological elements. But, this field of study has no proper scientific evidence, which is generally considered pseudoscience, or a scientifically questionable practice, which is still a contentious area because there is no standard. Most handwriting interpretations are made subjectively by professional graphologists.[1]

Various research studies show that handwriting and the neurological activities of humans are connected.[2] The first-ever non-invasive architecture that predicts the Big Five personality traits of an individual showed that this method achieves the highest prediction accuracy compared to state-of-the-art methods, enabling it to be the faster approach than psychological interviews or questionnaires for determining the Big Five personality traits.[3] With this being one side of the coin to analyzing the personality traits of humans, yet another important method to determine the people's personality traits is to predict their personality based on their behavior on social media platforms. The researchers analyzed human personality traits based on text data available on social media platforms.

The trends in social media made clear that social media had 3.8 billion active users in January 2020 and is expected to have a 9.2% growth in active users every year.[4] More precisely, the total numbers of users using Social Media (SM) platforms through LinkedIn are 917 million, more than 22 billion users through YouTube, and 2.86 billion users through Instagram.[4] Also, due to covid-19 and its related outbreaks, the only way through which users can interact with each other is through social networking. Studies[5–10] has shown that users' personalities and dynamic online behavior exhibit a robust correlation. People's usage of social media to express their views related to politics, movies, finance, societal interactions, and the well beings of their near and dear can be a more significant source to describe an individual's behavior and personality.

Some fundamental daily processes, such as temperament management, and information gaining have been influenced by human personality traits.[11] Personality traits describe an individual's relatively

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stable qualities that show the preferences and may control the individual's actions and are used in network security, finance, and political science methodologies.[12] Understanding user personality traits from social media text can be considered an information classification task. The social media text data provided by the users can give valuable, significant intuition on personalities (identifying the real "you," preferences, work-life balance, satisfaction levels in different aspects of life) if classified through accurate automated classification systems. These systems can be used in applications like counseling systems, personality detection systems, recruitment agencies, and online marketing, to name a few.[13,14]

The evolution in Natural Language Processing (NLP) has made many things possible to date that can be used to deal with the opinions expressed by online users on social media platforms for personality prediction despite inherent ambiguities in natural language. It is observed that the NLP research community has focused widely on Automated Personality Prediction. The main aim of personality detection is to make the psychological theory types useful and understandable in human beings' lives. Users can assess their personalities based on several online assessment facilities like Enneagram, career test, MBTI, BIG5, and DISC.[15] However, they are time-consuming and are not regarded as scientific assessment procedures.[16] Hence, for predicting personalities, many researchers used machine learning and deep learning algorithms to escalate the accuracy of the classification models. However, these algorithms' inability to extract contextual features of a sentence and out-of-vocabulary problems while using pre-defined corpus has led to many limitations. One of the significant obstacles to improving the model performance is the lack of a sufficient number of samples in the dataset for constructing an efficient personality prediction system.[13,17,18] Many other researchers have proposed sentiment-aware approaches for personality detection.[19] Another method is to build a model that is averaged on different pre-trained language models to improve the model accuracy.[20] These approaches are developed keeping in mind the limited amount of data available for personality prediction. If ever there is no problem with data availability, the research would have taken another turn.

The main contribution of this work is summarized as follows:

1) This research proposes a novel multi-model architecture for deep learning algorithms using a pre-trained BERT model with enhanced feature extraction using dataset mapping.

2) Earlier approaches added the sentiment, emotional, and additional NLP features and model averaging (due to less availability of data samples) to improve the model's accuracy. However, the proposed model in this paper creates highly effective, reliable data for working with deep learning algorithms by combining the two benchmark datasets (MBTI and Big Five datasets) for effective personality prediction.

3) The proposed model (the basic model with enhanced data representation) surpasses all previous model performance measures with different pre-trained language models. It is even on par with the state-of-the-art models created with combined sentiment and emotion information.

Literature Review

This section presents a critical literature survey of text-based personality traits.

Personality Detection using Machine Learning Algorithms

Several supervised, unsupervised and semi-supervised machine learning algorithms employ different techniques to Work on Personality detection. The corpus-based approach, termed the supervised approach, needs the corpus to be annotated for the classifiers to be trained and tested, which is a significant drawback of these techniques.[21] Different Machine Learning (ML) classifiers were employed by Chaudhary *et al.* using the MBTI dataset to predict the user's personalities from the data available online, where Logistic Regression (LR) gave 66.5% accuracy for MBTI types.[22] Another approach derived MBTI data from Reddit social media, which performs classification using SVM and LR, outperforming the previous methods. But this dataset contains many words in posts, which can sometimes affect the accuracy of the model due to the existence of noisy strings. The approach by Arroju *et al.* proposes a multilingual predictive model based on Twitter tweets, recognizing the user attributes with 68.5 % accuracy.[23] Alam *et al.* used Facebook status text to automatically detect personality traits using the Big Five personality model.[5]

Personality Detection using Deep Learning Algorithms

This section gives an overview of personalities assessed in two primary domains. The first is personality assessment using diverse platforms, and the second is personality assessment using social media as a major platform.

Personality Detection on Diverse Platforms

This paper outlines the related work done on MBTI and BIG 5 personality models, as our analysis is carried out on these models. More profound intuition into these models is given in the further sections of the paper. In recent years, personality detection using emails has been performed by Ezpeleta *et al.* using MBTI dataset that used Bayesian classifier for predicting personalities and sentiments.[24] Mobile Technology is another platform in which correlation and clustering methods are used to detect the Extroversion and Neuroticism traits using the BIG5 personality model.[25] Handwriting is considered one of the different ways to assess personality. Thomas *et al.* used Convolutional Neural Networks (CNN) to find the correlation between human handwriting and personality detection using the BIG5 model.[26]

Personality Detection on Social Media Platforms

Recent technological advancements enable deep neural networks for personality traits analysis. This section summarizes the work of different researchers who analyzed personalities on Data made available on the social media platforms using different techniques. Cost-effective neural network architectures and models have been developed rapidly in recent times, which made feature extraction feasible. A Bi-RNN-based word vector model is used by Liu *et al.* for word vector representations for predicting the Big Five personalities.[27] The effect of implementing different activation functions using CNN is performed by Rahman *et al.* and found that tanh activation performed better when compared to sigmoid and LeakyReLU for personality detection using text.[28]

The latest research on personality traits[19,20] using the pre-trained BERT model and its extensions have given many insights to analyze personalities deeply. Ren *et al.* developed sentiment-aware deep learning method for detecting personalities using text. Experimentation is done using BERT (single-label), BERT (multi-label), BERT and GRU (multi-label), BERT and LSTM (multi-label), BERT and CNN (multi-label), BERT with sentiment and CNN (multi-label). Of all these, BERT with sentiment and CNN (multi-label) has given the best performance for accuracy with 79.94% for Extroversion (EXT), 80.14% for Neuroticism (NEU), 80.30% for Agreeableness(AGR), 80.23% for Conscientiousness (CON), 80.35% for Openness(OPN), when the Big Five dataset has been considered for experimentation. More recent research includes model averaging of deep learning architectures[20], which detects people's personalities from data available on multiple social media platforms like Facebook and Twitter. Additional NLP features are also added to the model for better performance.

Research Objectives

After performing a detailed analysis of the existing contributions, this paper has defined the following research objectives.

1. To propose a new dataset that combines both the MBTI dataset and the Big Five dataset Personality correlation descriptors to convert the features of the MBTI dataset into the Big Five model.
2. To develop a new personality detection model that combines pre-trained BERT model and dataset obtained using mapping algorithm which increases the amount of data samples in personality dataset with appropriate personality labels.
3. The proposed approach creates a standard dataset with a large number of samples which makes it feasible to work with deep learning algorithms for better results. The dataset obtained will be made publicly available and it becomes a benchmark dataset for future research in the field of personality detection.

Materials and Methods

Proposed Methodology

The research takes its form in three different stages. Data Collection initiation is the first step, model development is the second, and finally, evaluation of the model is done in the third stage. The focus is on using two datasets, the first dataset is the MBTI dataset[29] and the second dataset is the Big Five dataset, taken from Majumder *et al.*[30]

1) The MBTI Dataset was developed by Myers (1962). The fundamental goal was to make type theory discoveries available to individuals and groups. Representation of personalities uses four dichotomies as an objective measure of Jung's theory of psychological types. It consists of four internally consistent but uncorrelated personality traits, namely,

i) Introversion (I) – Extroversion (E)
ii) Intuition (N) – Sensing (S)
iii) Thinking (T) – Feeling (F)
iv) Judging (J) – Perceiving (P)

A four-letter code gives a person's psychological type (e.g., INTP) and there are 16 different personality types[31] as shown in Table 1.

The Pearson correlation coefficient is calculated for the experimental data to ensure that the four dichotomies of the MBTI dataset are internally consistent but uncorrelated. The Pearson correlation coefficient measures the linear correlation between two sets of data. When the range of the correlation values is from −0.3 to 0.3, we can say that the two sets of data are not correlated as shown in Table 2.[(32)] The Table depicts that there is no correlation between the four dichotomies.

2) The Big Five dataset. The Big Five dataset used in this research is taken from James Pennebaker and Laura King's stream-of-consciousness Essay dataset.[33] A dataset named myPersonality, which had the data of 250 users with 9917 status texts, is the largest dataset in the field of analyzing personality traits, but, unfortunately, discontinued in April 2018, and authors decided to stop sharing the data even for academic research purposes for various reasons.[34] We considered taking the Essays dataset, having the Big Five personality dimensions as shown in Table 3. The Pearson correlation coefficient for Big Five (essays dataset) is shown in Table 4.

Analysis of MBTI Dataset: As already stated, the psychological type of every person is given by a unique four-letter code in the MBTI model. However, due to the lack of representational capability (bimodal distribution) of preference scores, the MBTI personality model has been prone to criticism.[35] Lack of support for typological theory is another reason for its criticism, besides having low construct validity.[36] Based on the distortions mentioned about the MBTI personality model, attempts were made to reinterpret the MBTI model from the Five-Factor Model (FFM) perspective.[37,38] Tadesse *et al.,* Yuan *et al*. discussed Personality prediction with respect to the contents in social media platform based on user generated content. [39, 40] An overlap between the personality measures of the two personality models is found. The correlations are shown in Table 5.

Analysis of data from Table 5 shows that Extroversion is correlated with E-I, Openness with S-N, Agreeableness with T-F, Conscientiousness with J-P, and Neuroticism with E-I. We further summarize the correlations in Table 6. An observation from Table 6 is that the correlation of Neuroticism with E-I is smaller in magnitude than the remaining correlations. The implications from this correlation

Table 1 — The 16 personality types of the MBTI®

ISTJ	ISFJ	INFJ	INTJ
ISTP	ISFP	INFP	INTP
ESTP	ESFP	ENFP	ENTP
ESTJ	ESFJ	ENFJ	ENTJ

Table 2 — Pearson coefficients (MBTI dataset)[19]

	IE	NS	TF	JP
IE	1	− 0.046	− 0.070	0.160
NS	NA	1	− 0.081	0.015
TF	NA	NA	1	− 0.00447
JP	NA	NA	NA	1

Table 3 — Some important characteristics of big five personality traits

	OPN	CON	EXT	AGR	NEU
High	Highly Creative, open to new things, focuses on challenges	Pays attention, planning, prepared	Likes attention, Energized in society, Easy to mingle	Happy to help, concern, contributes to peoples happiness	stressed, upset, mood swings
Low	Doesn't like changes, resistant, usual	messy, un organized, no discipline	solitude, cautious, do not favor exposure	Not interested to help, insulting, manipulates	Emotionally stable, No worrying, relaxed

Table 4 — Pearson coefficients (Big Five-Essay dataset)[19]

	EXT	NEU	AGR	CON	OPN
EXT	1	− 0.16	0.12	0.13	0.079
NEU	NA	1	− 0.089	− 0.148	−0.047
AGR	NA	NA	1	0.134	0.018
CON	NA	NA	NA	1	− 0.027
OPN	NA	NA	NA	NA	1

Table 5 — Partial correlations between MBTI factors and big five personality traits[37]

	E	I	S	N	T	F	J	P
NEU	−0.30	0.31	0.15	−0.14	−0.13	0.12	0.07	−0.07
EXT	0.71	−0.72	−0.28	0.27	0.00	−0.00	−0.13	0.16
OPN	0.28	−0.32	−0.66	0.64	−0.17	0.13	−0.25	0.26
AGR	−0.02	0.02	0.01	−0.00	−0.41	0.28	0.05	−0.06
CON	0.13	−0.13	0.10	−0.13	0.22	−0.27	0.46	−0.46

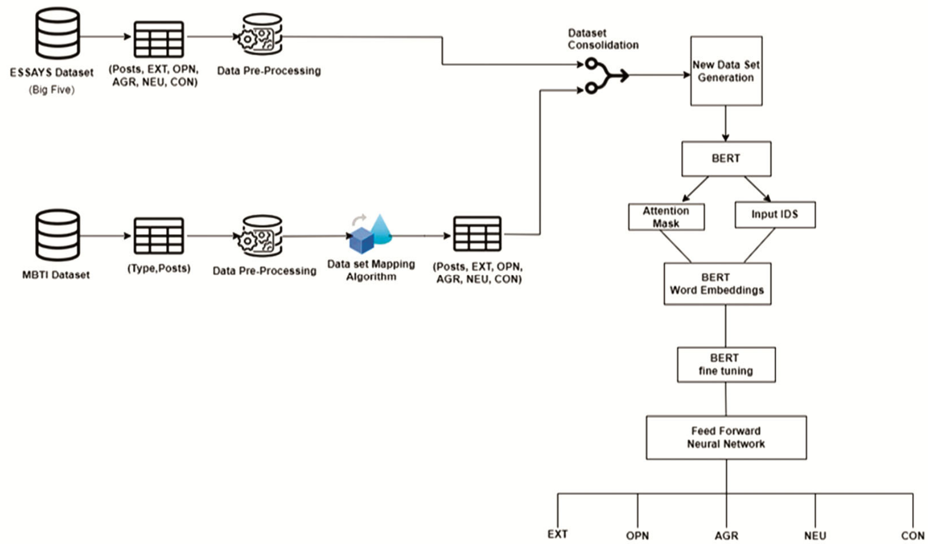

Fig. 1 — Flowchart for conducted methodology

Table 6 — Mapping based on Pearson coefficients between big five and MBTI factors

Big Five	MBTI	Correlation Score	Type of Correlation
EXT	Extroversion(E)	0.71	Positive
	Introversion(I)	−0.72	Negative
OPN	Intuition(N)	0.64	Positive
	Sensing(S)	−0.66	Negative
AGR	Feeling (F)	0.28	Positive
	Thinking (T)	−0.41	Negative
CON	Judging(J)	0.46	Positive
	Perceiving (P)	−0.46	Negative
NEU	Introversion(I)	0.31	Positive
	Extroversion(E)	−0.30	Negative

analysis clearly show that MBTI and the Big Five personality models can be combined to get an even clearer picture of personality traits.

Even though the correlation of NEU with E-I is −0.30 and 0.31, respectively, we consider it to be correlated, as the sub-factor of NEU (N4: Self-conscious) has a positive correlation (0.45) with I, and a negative correlation (−0.44) with E. From the above analysis, it is evident that we can map the features of the MBTI Dataset into Big Five Dataset. Using this, we propose a new methodology to create highly effective, reliable data for working with deep learning algorithms by combining the two benchmark datasets (MBTI and Big Five datasets) for effective personality prediction. The details regarding the stages of the methodology conducted is depicted in Fig. 1.

In Table 7, the proposed Dataset mapping algorithm is described. The algorithm's goal is to map the samples in the MBTI Dataset into the Big Five dataset. To achieve this goal, we need to analyze the MBTI dataset first. The dataset contains two columns, with the 'type' column being the first, which gives the user's personality type among the 16 different personality types (e.g., INFP, ENTP, Etc.). The second column, 'posts,' has the tweets tweeted by the users and is represented using Eqs (1) & (2).

$$S = \cup_{i=1}^{N} a_i = f(type, posts) \quad \ldots (1)$$

$$S_t = type \quad \ldots (2)$$

where, S , is the Total number of samples in the MBTI Dataset, $type$ is the personality type and $posts$ are the tweets tweeted by users and, S_t represents the sample that belongs to a particular personality type of MBTI dataset, with type being one among 16 personality types as in Eq. (3).

$$type = \begin{Bmatrix} ENFJ, ENFP, ENTJ, ENTP, \\ ESFJ, ESFP, ESTJ, ESTP, \\ INFJ, INFP, INTJ, INTP, \\ ISFJ, ISFP, ISTJ, ISTP \end{Bmatrix} \quad \ldots (3)$$

Next, the Big Five personality traits are taken as targets for the new dataset, and these targets are the new columns of the MBTI dataset that are being mapped to Big Five personality traits and are shown using Eq (4). Using Eqs (5) – (8), Table 7(a) describes the feature conversion algorithm.

$$T = [EXT, OPN, AGR, NEU, CON] \quad \ldots (4)$$

$$Pearson_{corr} = \frac{cov(X,Y)}{\sigma_X \, \sigma_Y} \quad \ldots (5)$$

$$y_{max} = \max\,(Pearson_{corr}) \quad \ldots (6)$$

Table 7 — Pseudocode for dataset mapping algorithm

Input: MBTI dataset (Personality representation with four dichotomies), Five Personality Traits from Essays (Big Five) dataset as target labels.

Output: MBTI Dataset Mapped to Big Five Personality Traits.

1. Use Eq. (2) and Eq. (3) to initialize df (Dataframe) with data from MBTI dataset;
2. Create $\boldsymbol{T}$ for each personality type as in Eq. (4);
3. Initialize result as an empty array
4. for value v in $\boldsymbol{S_t}$ do
   Use Table 5 to compute types_values[v] and append to result array
   end for
5. Initialize a New Data frame (df_target) for result array with $\boldsymbol{T}$ as target labels;
6. Drop $\boldsymbol{S_t}$ from df;
7. Concatenate df and df_target;
8. Generate mapped, consolidated dataframe df_mapped that has targets $\boldsymbol{T}$;

Table 7(a) — Pseudocode for Feature conversion

Input: MBTI Personality type.

Output: types_values.

1. Use Eq. (5) to Compute $Pearson_{corr}$ (Big Five, MBTI)
2. for Trait T in Big Five do
   Compute maximum y_{max} and minimum y_{min} values of Eq. (5) using Eq. (6) & (7)
   Use Eq. (8) to compute result end for
3. for Personality_categories P_c in MBTI do
   for personality_type P_t in P_c do
   if result $[P_t]$ = =”positive”
   Label T as “Yes”
   else
   Label T as “No”
   end if
   end for
   end for

$$y_{min} = \min\,(Pearson_{corr}) \quad \ldots (7)$$

$$result(x) = \begin{cases} positive, x\ is\ maximum \\ negative, x\ is\ minimum \end{cases} \quad \ldots (8)$$

This Illustration gives the mapping procedure of samples in MBTI with the Big Five traits. Consider ISTJ as an example personality type. From Table 6, Introversion (I) in MBTI is negatively correlated with Extroversion (EXT) in Big Five. So the corresponding label for I, after mapping with EXT, is NO (represented by the letter ‘n’ in the dataset). Sensing (S) in MBTI is negatively correlated with Openness (OPN) in the Big Five, so the label will be NO. Thinking (T) in MBTI is negatively correlated with Agreeableness (AGR) in Big Five, so the label will be NO. Judging (J) in MBTI has a positive correlation with Conscientiousness (CON) in the Big Five, so the label will be YES (represented by the letter ‘y’ in the dataset). As MBTI has only four dimensions, but Big Five has five-dimensional personality representations, the question is how to give the fifth label to the MBTI data sample.

Table 8 — Mapping ISTJ (MBTI) type into big five personality Traits

	EXT	OPN	AGR	CON	NEU
ISTJ	NO	NO	NO	YES	YES

Table 9 — Mapping MBTI type into Big Five personality

```
types_values = {
'ENFJ': ["y", "y", "y", "n", "y"], 'ENFP': ["y", "y", "y", "n", "n"],
'ENTJ': ["y", "y", "n", "n", "y"], 'ENTP': ["y", "y", "n", "n", "n"],
'ESFJ': ["y", "n", "y", "n", "y"], 'ESFP': ["y", "n", "y", "n", "n"],
'ESTJ': ["y", "n", "n", "n", "y"], 'ESTP': ["y", "n", "n", "n", "n"],
'INFJ': ["n", "y", "y", "y", "y"], 'INFP': ["n", "y", "y", "y", "n"],
'INTJ': ["n", "y", "n", "y", "y"], 'INTP': ["n", "y", "n", "y", "n"],
'ISFJ': ["n", "n", "y", "y", "y"], 'ISFP': ["n", "n", "y", "y", "n"],
'ISTJ': ["n", "n", "n", "y", "y"], 'ISTP': ["n", "n", "n", "y", "n"]}
```

The approach used is, among all the 16 types of personality traits in MBTI, eight types have Introversion (I) as the base personality of the form IXYZ, where X is either N or S, Y is either F or T, and Z is either J or P. Similarly, the remaining eight types have Extroversion (E) as the base personality of the form EXYZ, where X is either N or S, Y is either F or T and Z is either J or P. So, all the types which have I as the first letter are marked YES (positive correlation) for Neuroticism (NEU) in Big Five dataset, and the remaining types which have E as the first letter are marked NO (negative correlation) for Neuroticism (NEU) in Big Five dataset. Thus, the final mapping looks as follows for ISTJ personality type, as shown in Table 8.

All the 16 personality types of MBTI are mapped onto Big Five personality traits using the correlations from Table 6. The complete mapping is shown in Table 9 (“n” represents not correlated, “y” represents correlated).

After mapping the MBTI features into Big Five features, the obtained data is a complete dataset that uses the Big Five personality traits. Thus, a model is developed that can detect and classify a person's personality effectively. Here, a person with a high value for a particular personality will be given a number one (for Y) or else number zero (for N), which acts as a predictor variable for the model building in the later stage for all the traits in the Big Five model.

Data

The first Dataset is MBTI Dataset. Researchers use the MBTI dataset for personality detection, and it is the largest publicly available dataset. Twitter’s MBTI

Table 10 — Dataset details

Source	Dataset Name	Personality dimensions	Dataset Size	Content
Twitter	MBTI	four- dichotomies: I-E, S-N, T-F, and J-P	8675 × 50 (posts, type)	Each post has 50 consecutive Twitter texts from a particular online user
Essays	Big Five	five-dichotomies: EXT, NEU, AGR, CON, OPN	2467 × 50 (essay, type)	Each sample has multiple user sentences.

Table 11 — Dataset distribution after mapping

Dataset	MBTI (Twitter)*					
Category	Train		Test		Validation	
Label	Yes	No	Yes	No	Yes	No
Extraversion	62394	206467	13371	44242	13372	44243
Openness	232415	36444	49804	7810	49805	7811
Agreeableness	145391	123468	31156	26458	31157	26459
Neuroticism	206465	62394	44243	13371	44244	13372
Conscientiousness	106726	162135	22870	34743	22871	34744
Dataset	Big Five (Essays)					
Extraversion	886	826	190	177	191	178
Openness	851	857	184	185	185	186
Agreeableness	910	802	195	172	196	173
Neuroticism	871	841	187	180	188	181
Conscientiousness	880	832	189	178	190	179

*After Mapping MBTI Dataset into Big Five dataset

personality dataset is collected from the Personality café forum. It has 50 tweets of 8675 users and their personality labels, which further gives 422,845 labeled data points of the form (posts of users, type of the personality), which is made publicly available on the Kaggle website and can be used for academic research purposes.

The second Dataset is the Essays dataset. The Essays Dataset contains a total of 2468 author-tagged, anonymous articles with the Big Five personality dimensions: OPN (Openness), CON (Conscientiousness), EXT (Extroversion), AGR (Agreeableness), and NEU (Neuroticism). A sample in the Dataset has "Err: 508″, and hence, experimentation is carried out using 2467 data samples. Dataset details are shown in Table 10.

The two datasets are categorized into three sets. Training set (70%), test set (15%) and validation set (15%). The distribution of data in these categories is shown in Table 11.

Data Pre-Processing

Before performing feature extraction, the two datasets are pre-processed for efficient processing by the model. Aiming to increase the extracted features which results in more contextual features is the primary goal of pre-processing.

As a first step, the entire URL links have been removed. The sentences containing contractions such as I'll are expanded to I will. Next, all the sentences are normalized by converting them to lowercase letters. Later the usage of the NLTK package is done to remove stop words and clitics. In the MBTI dataset, additionally, the particular words which contain personality types in tweet texts are also removed. Many essential steps like removing multiple full stops, removal of non-words, and removal of multiple letters repeating words have been carried out. As a final step, sentences with less than three words are removed, as they cannot imply the personality of a person using only two words. Performing this particular step has shown a significant difference.

Feature Extraction

In this research, BERT, a language representation model, pre-trained on a vast number of unlabelled text corpus over different pre-training tasks, as proposed in Jacob *et al.* is used.[41] The architecture of BERT is designed so that it does the initial modeling of unlabelled text in both ways, where the context of each token in the sentences is combined from left to right and right to left in every layer.[42] 42More precisely, BERT uses both previous and next contexts to represent a particular word in a given sentence. The Fig. 2 helps visualize the feature extraction step using the pre-trained model.

As a first step, to provide the input, we took a sample sentence from the MBTI (twitter) dataset. This sentence will then be added with two unique tokens,

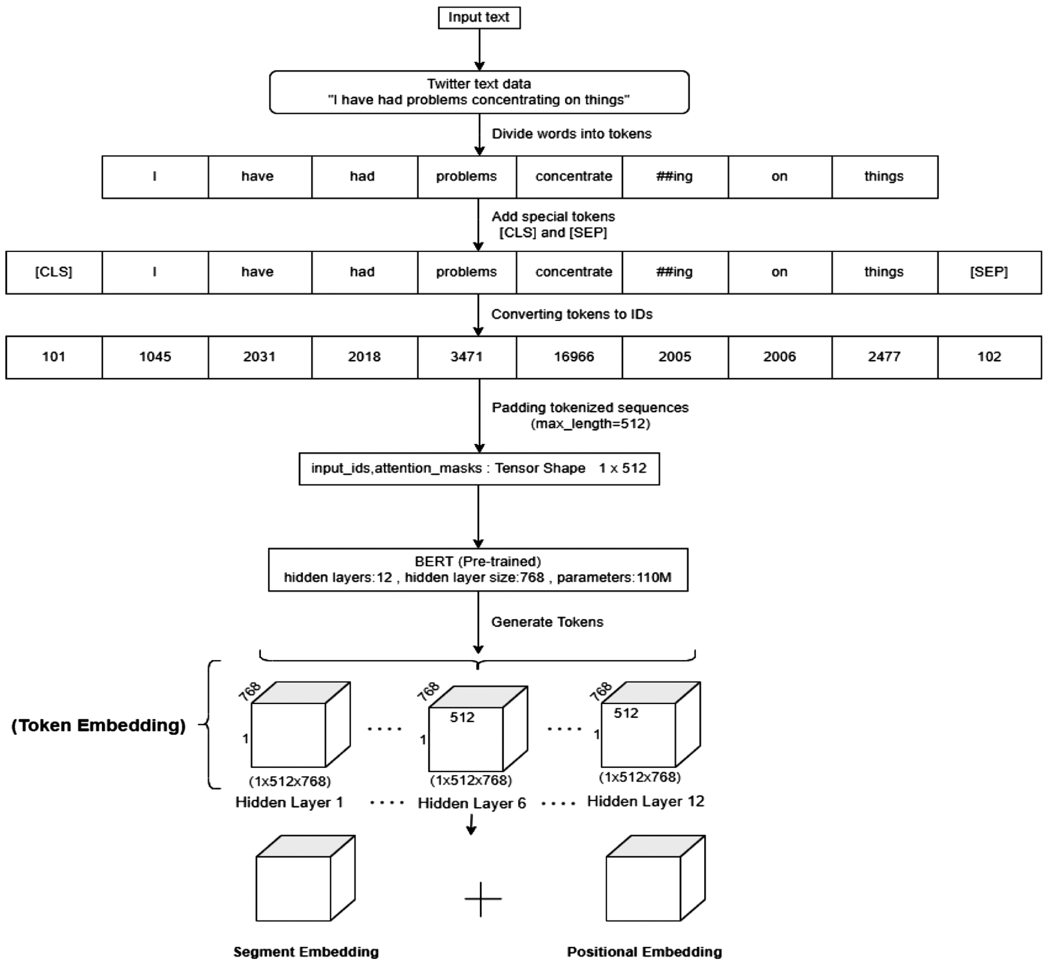

Fig. 2 — Feature extraction from Pre-trained model

[CLS] (classification token) at the beginning and [SEP] (separation token) as a separator at the end of the sentence, whose purpose is to separate sentences and mark the first token of every tokenized sequence. BERT uses Word Piece embeddings for tokenization, aiming to balance the vocabulary size and out of the vocabulary words. Later, the model pads the tokenized sequences up to a maximum length. Sequences with less than the maximum length are padded to meet the maximum length, whereas sequences with lengths more than the maximum length will be truncated. Next, the input IDs and attention masks are generated. Then, the pre-trained BERT model generates embeddings of 768 sized fixed dimensional vectors. Finally, the obtained embeddings are added to segment and positional embeddings to obtain context-related information into the model.

Model Prediction

Usage of Deep learning methods like CNN, LSTM, and Sentiment-aware approach, model averaging of pre-trained models like BERT, RoBERTa, and XLNet to study personality prediction has become widely popular in recent times. This study introduces a multi-label deep learning architecture by combining data mapping with predefined model features to obtain the best out of predicting personalities.

Input embeddings obtained from the pre-trained model are fed into the self-attention mechanism. To obtain self-attention, the input embeddings are fed into three unique connected layers for creating pairs of Query (Q), Key (K), and Value (V) vectors. The attention and reweight values are calculated independently in different heads. The reweighted values are calculated in every head as given in the following equation, a scaled dot product. Re-scaling by $\sqrt{d_k}$ is found to be effective.[40]

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \quad \ldots (9)$$

Five classifiers are used to predict personalities, where every single classifier output describes the Big

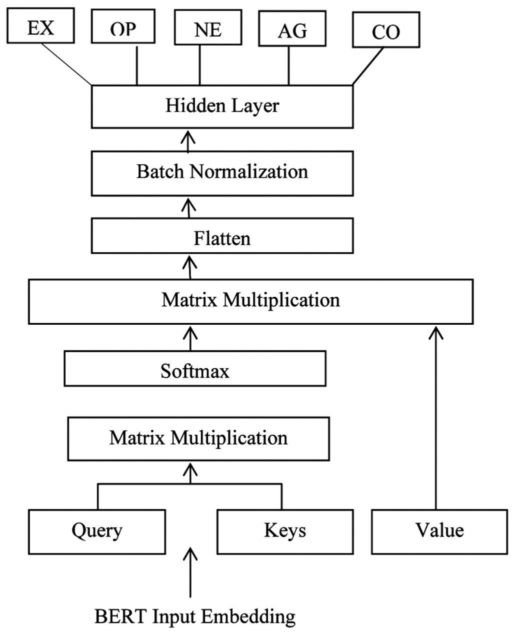

Fig. 3 — Proposed Model Architecture

Five personality traits. Fig. 3 depicts the model architecture. The loss function used is binary cross-entropy and is calculated as:

$$Loss = -(y log(p) + (1 - y)\log(1 - p)) \quad \dots (10)$$

where, y denotes actual label, p denotes predicted personality from the given input sentence. A hyperparameter tuning is carried out to find the optimal performance for better prediction by the model, with the hyperparameters being the number of epochs, learning rate, and batch size.

Evaluation Metrics

Results obtained from the model are evaluated using Accuracy and F1 measure score as follows:

Accuracy measures the model's performance by focusing on the total data that is predicted precisely, namely True Positive and True Negative. Many researchers use this as a metric for evaluation. This research also uses Accuracy to measure the performance of the model.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad \dots (11)$$

where, TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative. Another important measure is the F1 Measure, which is a function of Precision and Recall. Some persons can be placed incompatible with their personality. So it is important to reduce predictive errors by considering False Positives and False Negatives, which is done by F1 Measure, and is given as follows:

$$Precision = \frac{TP}{TP+FP} \quad \dots (12)$$

$$Recall = \frac{TP}{TP+FN} \quad \dots (13)$$

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \quad \dots (14)$$

Results and Discussion

This section discusses the experimental results. We use the Big Five personality model to compare our work with previously proposed methodologies that gave the best results. We consider two completely different datasets to assess the model's performance, namely MBTI (Twitter) and Essays (Big Five), for experimentation. The results of this research are presented and compared to state-of-the-art models. The results of evaluating the MBTI (Twitter) dataset converted to the Big Five Personality model combined with the Essays (Big Five) Dataset using the pre-trained BERT model is given in Table 12.

Openness has the highest accuracy with 86.24% accuracy and 91.56% F1 measure score. Second, the highest accuracy is found for Extraversion, with 76.77% accuracy and 75.29% F1 measure score. But, when Neuroticism is considered, the highest accuracy with 74.63% accuracy and 84.93% F1 measure score is obtained for MBTI mapped to Big Five Dataset. However, the average accuracy value and F1 measure score are higher for the proposed model with the Essays Dataset added to the mapped dataset. Next, Table 13 gives the training parameters results for the proposed model in terms of best-achieved accuracy and F1 measure score. Finally, Table 14 compares the proposed model with the state-of-the-art techniques. The proposed model improved the performance with 74.43% average accuracy for proposed method, whereas for the best baseline it is 74.20% and for average F1 score, the proposed model has 0.769, whereas for the best baseline it is 0.71. From Table 12, it is observed that when all the correlation descriptors are removed, the average accuracy and Average F1 score are 65.94 and 65.35. When dataset mapping algorithm along with data consolidation is performed, the average accuracy raised to 74.43% and average F1 score raised to 76.97%. This ablation study shows that, the parameters of MBTI and Big Five are correlated, and it is very helpful to take these correlations into account for the purpose of effective personality prediction.

Table 12 — Model Performance for personality prediction using data mapping

Traits	Metric	System baseline (BERT) (Essays-Big Five)	(MBTI→ Big Five)	Proposed Model (MBTI→ Big Five) + Essays
Openness	Accuracy	75.89	84.22	86.24
	F1 Measure	76.20	89.50	91.56
Conscientiousness	Accuracy	58.37	68.23	70.36
	F1 Measure	54.52	67.58	68.54
Extraversion	Accuracy	70.20	75.61	76.77
	F1 Measure	71.37	74.25	75.29
Agreeableness	Accuracy	56.45	64.67	65.02
	F1 Measure	60.21	66.13	66.46
Neuroticism	Accuracy	68.82	74.63	73.77
	F1 Measure	64.46	84.93	83.02
Average	Accuracy	65.94	73.47	74.43
	F1 Measure	65.35	76.47	76.97

Table 13 — Best Parameters for proposed model

Dataset	Batch Size	Learning Rate
(MBTI→ Big Five)	32	0.00002
(MBTI→ Big Five) + Essays	32	0.00002

Table 14 — Comparison Model Performance with state-of-the-art approaches (Facebook Dataset- Big Five Model)

Model	Average accuracy	Average F1
Tandera *et al.* [18]	70.40%	—
Zheng & Wu[38]	—	0.71
Tadesse *et al.* [39]	74.20%	—
Yuan *et al.* [40]	70.00%	—
Hans *et al.*[BERT] [20]	72.50%	0.688
Hans *et al.*[RoBERTa] [20]	71.85%	0.677
Hans *et al.* [XLnet] [20]	72.13%	0.683
Proposed Experimental Model	74.43%	0.769

Conclusions

The research mainly concentrated on improving the performance of the deep learning model by enhancing the dataset using a novel dataset mapping algorithm. This experiment reveals that the proposed model has produced high accuracy than the existing models with 86.24% accuracy for Openness, 70.36% accuracy for Conscientiousness, 76.77% accuracy for Extraversion, 65.02% accuracy for Agreeableness, 73.77% accuracy for Neuroticism, which is higher than the models in the literature of personality detection. This improvement is due to the large amount of data obtained by using a novel data mapping algorithm. The research's future direction will use other pre-trained models like RoBERTa, XLnet, and ALBERT. Later the authors aim to extend the study by adding the sentiment and emotional information to improve the model's performance. The new dataset obtained will be made available for researchers on request. Later this dataset might be the benchmark dataset for researchers in personality traits prediction.

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