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Application of machine learning using MBTI classification to understand the borderline disorder

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***Abstract*—The unique combination of features that define a person's habits, actions, attitudes, and thought processes is known as their personality. Based on supervised ML techniques applied to benchmark datasets, current research on social media text and personality detection uses these techniques. It may be tough to perform in routine activities if you've a borderline personality syndrome, a mental disorder that changes how you thinks and feel about yourself and other people. The primary goal of the current research is to infer user personality from the MBTI personality traits and predict the personalities which might be affected by borderline disorder. To extract personality characteristics, an intelligent sentence analysis model is created. Researchers have recently become interested in building automatic personality detection systems as a result of personality recognition from social networking sites. The main aim of this paper is to link personality classification with disorder, in our case we have chosen one of the common disorders which is borderline disorder. So, both the personality and the disorder are classified via Machine learning models. In this project, we'll be using 2 algorithms which are random forest (RF) and Decision tree (DT) to categorize the collected data into specific traits as well as to classify them if they have traces of borderline disorder. The accuracy scores of the algorithms respectively are 84% and 76.44%.**

Keywords- machine learning, personality recognition, borderline disorder, random forest, decision tree.

I. INTRODUCTION

Internet-based technology has become an essential component of daily life. Social media, which has merged seamlessly into our lives, has made communication simpler. Social media platforms like Instagram, LinkedIn, as well as Facebook rely on human interaction and data supplied by users. As a result of the increased number of users who create and exchange data, a large amount of interactive data is produced, which finally makes it interactive. A personality is defined by the characteristics that define a person, such as emotions, behavior, cognition, and temperament. Because there is no predetermined structure for identifying and comparing people, determining personality is critical. An introspective self-report questionnaire called the MBTI (Myers-Briggs Type Indicator) is utilized in personality typology to discover different psychological inclinations in how persons perceive their surroundings and make choices. Each of the following four types— sensing or intuition, introversion or extraversion, feeling or thinking, and perceiving or evaluating—is allocated a value in the test. Also, these days many youngsters fall into stress, depression, and various other psychological disorders. Certain personalities might by default be affected by certain disorders due to stress and other environmental factors. Detecting them early would help them to overcome their psychological issues. Because there are uneven classifications of personality characteristics, the performance of the existing approach for recognizing personalities might yet be enhanced. Moreover, it would be great if there was a system where we could predict personality traits and also borderline disorders. A wide range of objectives may be attained with personality evaluation, such as the identification and description of personality traits in healthy candidates and also the assessment of disturbed personalities in psychotherapy subjects. This work aims to connect personality classification with the disorder; in our case, we choose one of the most frequent disorders, borderline disorder. As a result, machine learning models are used to classify both the personality and the disorder.

II. LITERATURE SURVEY

Regarding the literature survey most of the papers were either personality classification centric or disorder centric.

We have gone through many research papers out of which the surveys of important papers are looked upon.

Jayaratne *et al* focused on helping hiring managers, recruiters, and applicants make better-hiring choices based on their capacity to evaluate a candidate's personality throughout the application process [1]. To self-rate their personalities, over 46,000 employment candidates engaged in an online chat interview with the researchers, who also administered a personality test based on the six-factor HEXACO personality model. In a second study with 117 participants, the accuracy of the trait-level personality descriptors based on the inferred trait scores was 87.83 percent.

Examining the predictability of Facebook user personality characteristics using multiple Big 5 model variables and features is the goal of this article [2]. Using the myPersonality project data set, they investigated whether social network structures and linguistic characteristics are present in personality interactions. They compared the four machine learning models, looked at how each feature set related to personality traits, and then interpreted the findings. The results of the prediction accuracy tests demonstrate that the personality prediction system based on the XGboost classifier surpasses the average baseline for all the feature sets, with the maximum prediction accuracy of 74.2 percent, even when tested using the same dataset. The individual social network analysis feature set yielded the best extraversion trait prediction result and had maximum accuracy of 78.6%.

In the paper of Mushtaq *et al,* we could see the integration of two well-known ML methods, Gradient Boosting, and K-Means Clustering, to determine a user's personality type by studying user data uploaded on social media [5]. The personality classification used was MBTI classification, and their machine learning approach performs better than other approaches including neural network-based models or Naïve Bayes classifier. Traditional Naïve Bayes had an overall accuracy of 85%, whereas LSTM-based models had an accuracy of 82%.

This study [7] compares several feature extraction techniques and algorithmic frameworks while developing personality prediction systems for multiple social media data sources. Using the Facebook dataset's highest accuracy of 86.17 percent and f1 score of 0.912 and the Twitter has the greatest accuracy of 88.49 percent and f1 score of 0.882, respectively, the suggested approach outperforms most personality model builds. These results come from an experiment. NLP statistical features sentiment analysis, like TF-IGM, and the NRC lexicon database were also added, which had a significant impact on the personality prediction system on both datasets. These features can improve performance in comparison to using only pre-trained models as extraction features.

The goal of the study [9] is to make personality predictions based on a person's extraversion, openness, neuroticism, agreeableness, and conscientiousness scores. We required a method to compute the scores straight from each CV to do this. This study utilizes a range of ML models, including Naive Bayes, Logistic Regression, RF, KNN, and SVM, to predict personality using CV Analysis. We were capable of predicting each candidate's personality using spaCy, pyparser, as well as Phrase Matcher. The findings show that Random Forest has the highest accuracy (0.71), however because of a lack of data, the accuracy is substantially lower than expected.

The potential and significant difficulties brought by modern personality measurement utilizing big data are examined in this conceptual work [4]. The article gives a brief overview of the many technologies that lead to big data as well as an overview of how big data is presently utilized in personality study and how it may be applied later, a methodological structure for using big data in personality psychology, an investigation of notions that relate psychometric validity and reliability, and standards of privacy and fairness, to indicators of personality that employ big data, and a debate highlighting the relevance of big data in personality research, and lastly, a summary of practical advice for academics seeking to enhance big data personality assessment and study. This publication is predicted to help personality researchers manage the potential and risks presented by adopting big data technologies for personality measurement by offering insights, advice, and inspiration.

III. RESEARCH GAPS

The MBTI model is more often used by researchers, and taking into account the debate about the validity and reliability of these two models, it is more applicable to various fields of study. Another thing noticed in the survey is that most of the papers have chosen Facebook posts to collect the data set and a few trained the model with existing datasets. The most recent studies on detecting personalities in social network text use benchmark datasets and controlled ML models. However, the skewness of the datasets, or the existence of imbalanced groups with diverse personality characteristics, is the basic problem. This concern is primarily accountable for the diminished effectiveness of personality recognition systems. One of the key points to note regarding the gap present in this area of the field is that these papers were either personality-centric or disorder centric. Also, these papers focus mainly on textual emotion to classify the personality.

IV. METHODOLOGY

A. Forming the dataset

Getting your data is the first step of model training as shown in Figure 1. The dataset must be accurate and authentic. There can be multiple sources of data like sensors, flat files, databases, data warehouses, social media websites, etc. We created a dataset based on post findings from a personality-based forum website to investigate personality traits from social networks. We built the study using 200 users and 5418 website status updates. The user dataset was labeled using the MBTI model. Depending on how personality types were distributed, every user in the dataset had several posts compiled into one file. The dataset has three columns: personality type, personality-based postings, and diseases listed in the posts.

B. Classifying the dataset

Four distinct categories were made for the type parameters to comprehend how they were distributed across the dataset. Feeling (F) and thinking (T), judging (J) and perceiving (P) and sensing (S) and Intuition (N), were the first, second, third, and fourth, respectively. As a consequence, one letter will be returned for each category, resulting in a final set of four letters that each reflects one of the MBTI's 16 personality types. In the case of the Disorder, the data samples collected have various combination Disorders such as borderline disorder, Depression, eating disorder, bipolar disorder, ADHD, OCD, PTSD, etc. for various users. In this case, it is a bit difficult to classify a person with any disorder. So as of now, we have just focused on borderline disorder only.

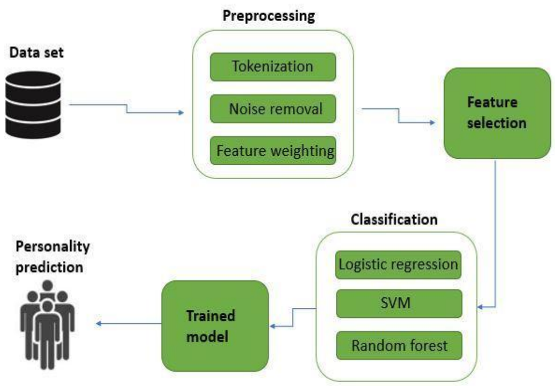

Figure 1. Architectural diagram of the proposed system

C. Pre-processing the dataset

As previously mentioned, the information in the dataset was acquired from a personality-based forum, and it became apparent through an analysis of the dataset's content that certain words needed to be removed. The main cause of this was a dataset's non-uniform representation of MBTI kinds, which was out of proportion to the proportions of these kinds in the general population. This was shown to be the case since the information was taken from an online forum where people discussed personality types and MBTI types were referenced much too often in the discussions. It is the same when it comes to the disorder part and various people are classified with various combinations of disorders. This may also have an impact on the model's accuracy.

The MBTI disorders and types were therefore eliminated from the dataset using NLTK. This was followed by another determination of the distribution of MBTI personality kinds in the dataset, with the result that the representation of MBTI kinds in the dataset now accurately reflects the size of the MBTI population. Also, all stop words as well as URLs were eliminated from the dataset. Finally, the text was lemmatized, which means that words' inflected forms were changed into their root words, to further improve the dataset's meaning.

D. Vectorization with term frequency-Inverse document frequency

We utilized the Sklearn package to find terms that were used between 10% and 60% of the posts. The initial phase was sorting postings into a token count matrix. In the next stage, the model returns a term-document matrix after learning the vocabulary dictionary. Then, a normalized TF-IDF representation appropriate for the RF model is created from the count matrix. Finally, 528 words can be found in 10% to 60% of the posts.

E. Developing models

Individual Borderline disorder and MBTI-type parameters were learned, and the data was then divided into testing and training datasets with the train_test_split () function of the sklearn package. A total of 70% of the data was utilized as the training data, while the remaining 30% was used as the test set. Testing data predictions were produced after the model corresponds to the training data. Since this project mainly focuses on combining personality with borderline disorder out of the 16 personalities, the types which have a high chance of this disorder are chosen. The performance of the DT and the RF model on the testing dataset during training was then assessed, and early stopping was tracked. Testing data predictions were produced after the model correspond to the training data. In this stage, the decision tree model and the random forest model's performance on the testing dataset were again assessed; the findings are shown in the result section.

V. RESULT

We tested the trained regression models on data with 30% of the data being in the test class. These models are assessed

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with the correlation coefficient between the actual (ground truth) and the projected trait values. After examining the significant correlations found between the two models, the Decision tree model and the Random Forest model, we carried out an experimental assessment using two baseline techniques and the Random Forest model as the main classifier. The table and Figure 2 below show the model's accuracies after training data and testing the data.

TABLE I. OVERALL ACCURACY SCORE FOR PERSONALITY PREDICTION WITH DISORDER

Model	**Accuracies**	
	Training	***Testing***
Random forest	100%	84%
Decision tree	96.57%	76.44%

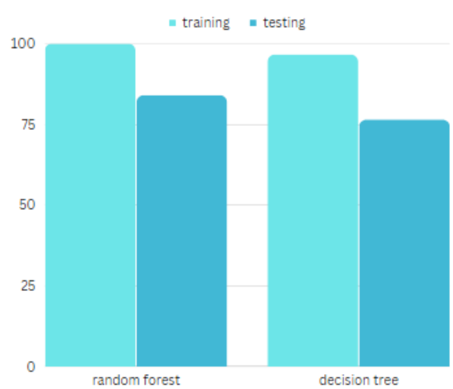

Figure 2. Comparison of accuracies of the models

Here is the confusion matrix result for the Random Forest model as shown in the figure below. In this work, we have chosen Borderline disorder to be classified based on the textual classification with the same models. Currently, we have just focused on classifying this particular disorder with the two models.

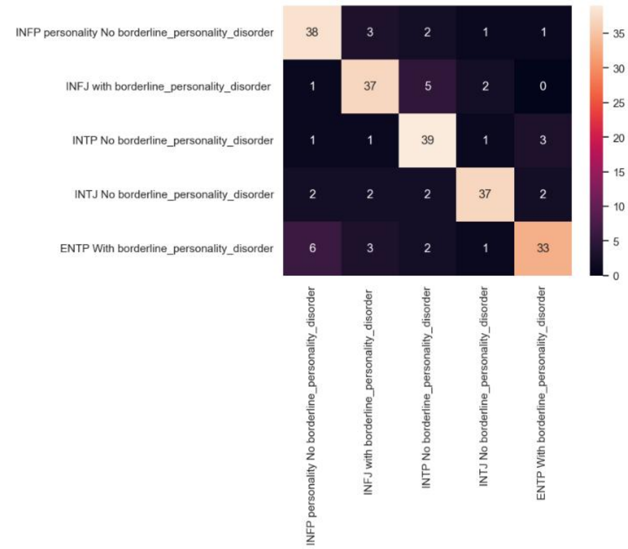

Figure 3. Confusion matrix of Random Forest

Following we have the confusion matrix for the decision tree algorithm.

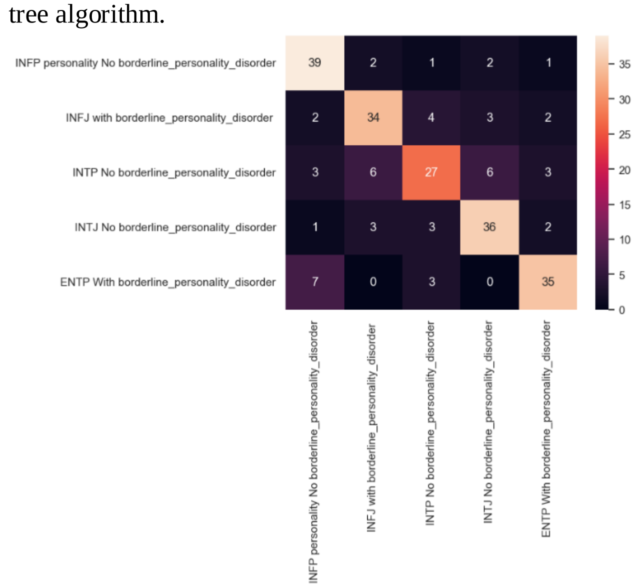

Figure 4. Confusion matrix of Decision tree

VI. CONCLUSION AND FUTURE WORK

We have explored potential features of MBTI personality and a part of borderline disorder. Additionally, it is clear how the ability of computers to objectively determine a candidate's personality based just on the text of their interview responses might remove the subjectivity inherent in human interviewers' assessments of a candidate's personality or psychopathology. Third, we have considered emotions and a few sensitive words as our features in the dataset to diagnose personality as well as borderline disorder. Last but not least for our dataset the accuracy rate was 76.44% for personality and borderline disorder classification using the Decision tree classifier and 84 % using the random forest classifier using the live data set collected. We only used posted messages (text) in this study; in the future, we will predict user personality from the dataset visuals. Extracting embedded contextualized words from textual data for use in prediction systems may be done in a variety of ways. There were some limitations, such as some algorithms' inability to grasp the semantic meaning of words, which is why we chose the particular models with the highest performance. In the future, it is required to find the optimum feature set for which the prediction is best for all. Another helpful potential extension of this study is to investigate if other sorts of characteristics, such as the usage of POS (parts of speech), use of emojis, formality, readability, etc., may further improve the accuracy. Also refining the dataset is crucial to increase the accuracy score of the algorithms. Predictions of the disorders are done based on the textual emotions as of now. In this study, we have focused only on borderline disorder. In the future, we can improvise the work by extending with various disorders and research more on the link between personality type and certain disorders.

To improve text-based inferences of personality and disease, multi-modal information, like video and audio signals obtained while applicants respond to questions, may be explored as signals. To do this, personality psychologists must continue to create and take part in multidisciplinary communities of interest centered on potential future developments in big data and ML. Trends appear to be trending in this direction; perhaps we can accelerate that trend by applying ML models to big data personality researchers themselves.

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