Persona Traits Identification based on Myers-Briggs Type Indicator(MBTI) - A Text Classification Approach

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***Abstract*—Personality is a very important part of our lifestyle. It determines how we live, speak, react, and indicates our preferences, and even affects our mental health. Personality analysis is an intuitive ability of humans, carried out every day with multiple people, and for innumerable reasons. Personality profiling, specifically, has several real-life use cases, such as mental health screening tests, screening during human resource interviews, recommendations to writers about the interplay between personalities that people enjoy reading about and friend suggestions. This work presents the analysis of text written by a person such as an essay, tweet, or blog post and creates a personality profile of the person. The main considerations of the work are the type of data gathered, text preprocessing methods, and the machine learning techniques used to estimate personality scores. Various machine learning models and feature vector combinations have been compared, and deployment of solutions have been described. Accuracies up to 88% were achieved using the methods detailed in this work.**

***Index Terms*—Myers-Briggs Type Indicator (MBTI), Computational Psychology, LIWC, EmoSenticNet, ConceptNet, SVD, SVM**

I. Introduction

Persona refers to the character played by a person or the character displayed by the person to the outside world. A person can have multiple persona. Persona can be identified from the text written by a person[8]. The main objectives of the work are:

- *Mental Health Screening Test*: The primary motivation behind the work is to identify mental health disorders, especially Depression, from text written by a person. Depression is a common mental health condition, that is prevalent in high-stress environments. This work helps to analyse and identify individuals who may be suffering from depression, in order to promote healthier and happier lifestyles, increase productivity, and in extreme cases, prevent suicide.
- It helps in recommendation of popular character combinations to authors, for fictional works.
- It helps Human Resource departments for screening of potential candidates, when candidates are required to fit a personality profile.
- It helps in recommending products or services, according to their reception by users with similar personality traits.

II. Background

Personality of a person can be analysed based on various traits or combination of traits displayed by a person. The Myers-Briggs Type Indicator (MBTI) is a questionnaire-based personality profiling theory, aiming to highlight psychological differences between individuals' perception of the world and decision making skills. This scale was designed for a regular population, and to distinguish between individuals occuring by nature. The MBTI scale provides a broad variation in personality classification by providing four personality classes. These four classes are further divided into sixteen personality types. The four MBTI classes are :

- *Extraversion vs Introversion* : This class indicates how outgoing a person is. Extraverted people are talkative and outgoing. Introverted people are reserved.
- *Sensing vs Intuition* : This class indicates how a person perceives information. It differentiates between people who focus more on trusting what is certain and people who prefer to make inferences based on patterns and impressions.
- *Thinking vs Feeling* : This class indicates the decision making ability of the person. An individual can either

use logical reasoning or be more empathetic in making decisions.

- *Judging vs Perceiving* : This class indicates the orientation of an individual to the outer world. An individual may either prefer being settled and organized, or spontaneous and flexible.

Combination of the above four classes provides 16 MBTI personality types as shown in Table I and Fig. 1.

E Extraversion	**N** Intuition	**F** Feeling	**P** Perceiving
I Introversion	**S** Sensing	**T** Thinking	**J** Judging

TABLE I
THE FOUR MBTI CLASSES

III. RELATED WORK

Personality can be categorized using many psychological systems, such as Myers-Briggs Type Indicator and Big Five. Commonly, the systems determine an individual's personality using questionnaires. MBTI was developed from the personality theories of Carl Jung, and intends to sort people into sixteen categories, depending on their psychological preferences. MBTI has become an important tool in several large scale scenarios, like gauging managerial skills such as risk tolerance and conflict management[15], bank management, career success, and has been found to have an effect on variations in making decisions, such as in university course selection.

In previously done research, it has been shown that data posted by a person can be used to predict an individual's personality effectively[14]. Also, text is indicative of the character traits of an individual, and analysis of the text can produce models to predict personality[4]. It was found that usage of Mairesse features[16] with deep convolutional neural network produced an accuracy of upto 63%, and was higher than results of using merely word n-grams[2]. With application of LIWC features on Facebook status updates, open vocabulary approaches were found to perform better than closed vocabulary approaches[1]. Feature reduction using Information Gain and PCA were beneficial, as they reduced the size of input data, while slightly improving accuracy of predictions[9]. Emolex was found to be effective in analysis of emotion of a sentence[3], and also ConceptNet was observed to improve personality prediction[13].

The research done till date involves creating personality profiles of individuals, by using only their choice of words. Due to this limitation, there is a lack of accuracy, as the current software cannot identify features such as sarcasm and irony. In addition to this, it does not account for emotional influences in sentences. Also, very little work has been done on MBTI personality types, which indeed provides a broad spectrum of personality combinations. This work aims to enhance the research scenario by constructing semantic representations, and using these to identify personality characteristics based on the MBTI personality scale.

IV. PROBLEM STATEMENT

Given social media posts, essays or blogs written by a person, the objective of the work is to analyse them and create a personality profile of the person, by scoring him or her on the MBTI scale using Computational Psychology. Computational Psychology is the branch of psychology that uses various techniques in Computer Science to analyse the behavior of an individual.

V. DATASET

The dataset used in the work consists of tweets tagged with one of the 16 MBTI types (Table I, Fig. 1). These tags are combinations of four characters. Each character corresponds to the first or second letter of the traits in the four MBTI classes. The dataset consists of 8660 rows. The distribution of MBTI traits(number of rows out of 8600) in each class is as follows:

- *Introversion(I)* : 6664; *Extraversion(E)* : 1996
- *Sensing(S)* : 7466; *Intuition(N)* : 1194
- *Thinking(T)* : 4685; *Feeling(F)* : 3975
- *Judging(J)* : 5231; *Perceiving(P)* : 3429

The text in a particular row consists of tweets from an individual user (Table III). Sentiment analysis of the dataset indicated that (i) In general, tweets seem more positive than negative or neutral (ii) ISTP (Table I, Fig. 1) seems to be the most negative and least positive among the MBTI types (iii) Least negative was ESFJ (Table I, Fig. 1), most positive was ENFP (Table I, Fig. 1), least neutral was ENFJ (Table I, Fig. 1), most neutral was ESFP (Table I, Fig. 1). Analysis of trend in emotions indicated that most MBTI types(Table I, Fig. 1) display positive, trust and anticipation emotions. Table II shows the statistics of the dataset.

Average number of tweets per user	49
Average number of words per user	1310
Average number of characters per user	6600
Average word length across the tweets per user	4

TABLE II
STATISTICS OF THE DATASET

VI. RESOURCES

In order to explore the personality traits from text written by individuals, various resources have been used for preprocessing the text in addition to applying Natural Language Processing techniques. These resources are used to construct semantic and emotional representations of the text, which are passed into the training modules.

The resources used are:

- *LIWC(Linguistic Inquiry and Word Count)*: LIWC is a gold standard in computerized text analysis. It captures the contribution of everyday words towards revealing thoughts, feelings and personality of a person. It consists of more than eighty linguistic, psychological and topical categories. It is accurate and easy to use.

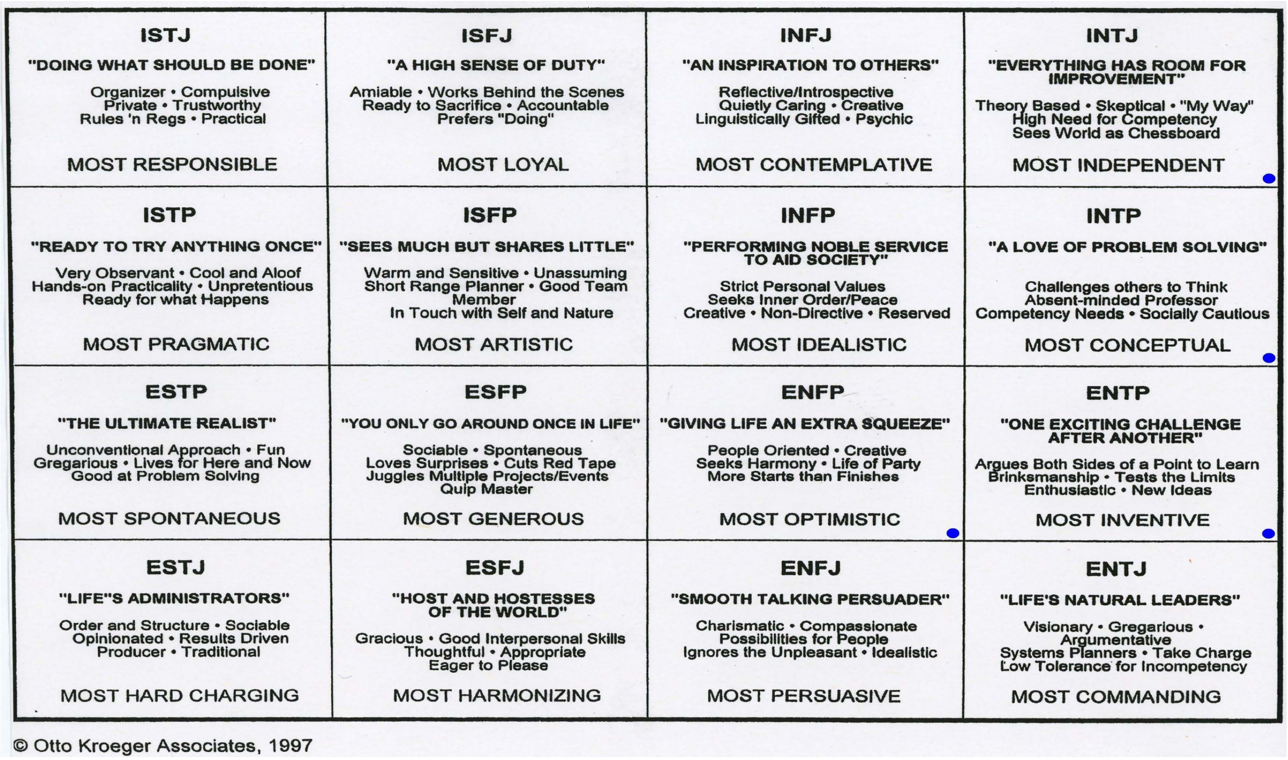

Fig. 1. The 16 MBTI Types

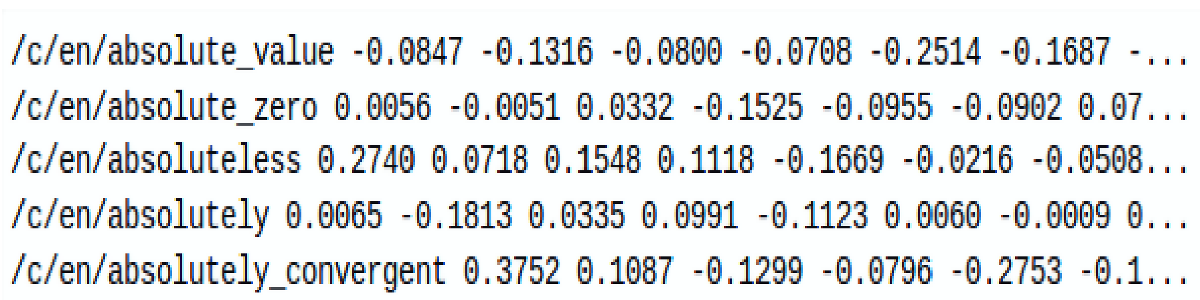

Fig. 2. English Numberbatch - ConceptNet

- *EmoSenticNet or Emolex*: EmoSenticNet[3] is a lexical resource that assigns eight emotions and two sentiments to a word, based on the emotion conveyed by the word.
- *ConceptNet*: The ConceptNet[5] represents the information derived from the Open Mind corpus in the form of a directed graph, where the nodes represent concepts and the labeled edges represent common-sense assertions which connect them. For example, assuming the two concepts *whale* and *swim*, an assertion between them is *CapableOf*, i.e. a *whale is capable of swimming*.

VII. Methodology

This section describes the methodology followed to obtain the personality scores on the MBTI scale (Fig. 3).

A. *Preprocessing*

Hyperlinks, numbers and punctuations are removed from tweets (Table III). WordNet Lemmatizer is used for lemmatization and Lancaster Stemmer is used for stemming of the tweets. Tweet Tokenizer is used to tokenize the tweets[6]. The tweets are represented using the top 1500 most frequent words.

B. *Feature Vector Generation*

NRC-Emotion-Lexicon-Wordlevel-v0.92[3] is used to generate the Emolex vector. Each word in the lexicon is tagged with eight emotions and two sentiments namely, anger, anticipation, disgust, joy, surprize, fear, sad, neutral, positive and negative. Zero or one is asssigned to an emotion if a particular word depicts that emotion. The words in the dataset are tagged with the emotions based on their occurence in the lexicon. The

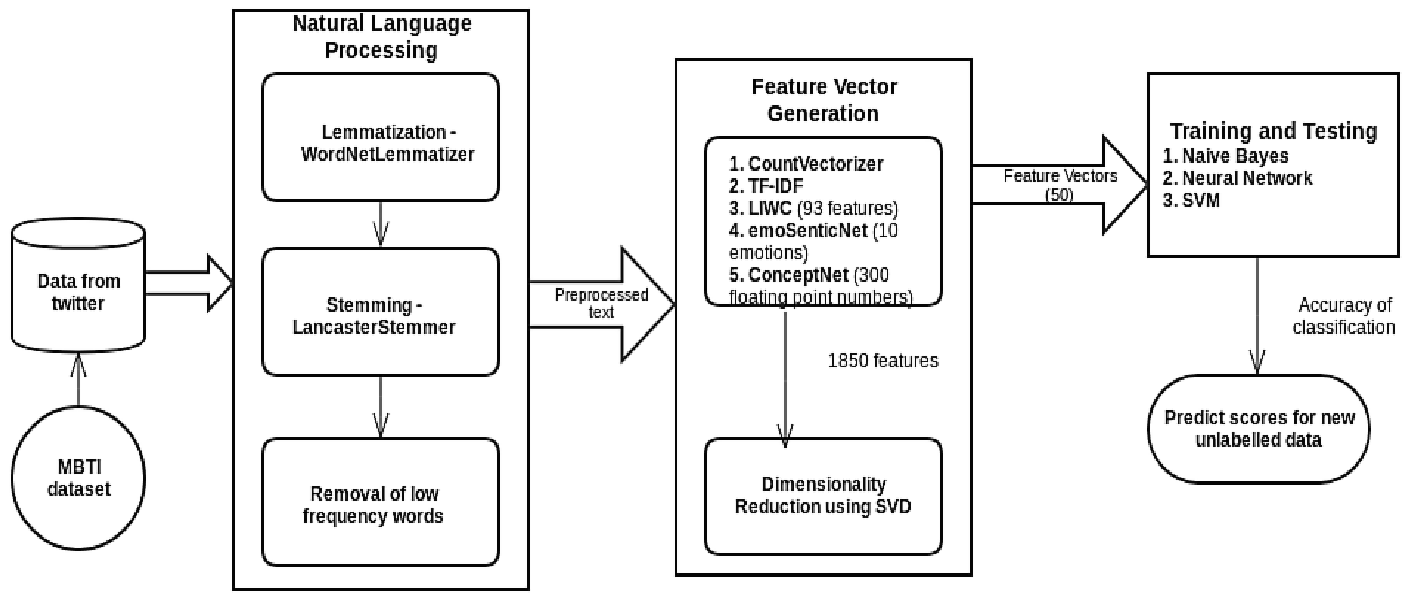

Fig. 3. MBTI Classifier Training Scheme

emotion vectors of each word in a set of tweets of a particular individual are combined using component-wise summation. LIWC features are obtained using the student version of LIWC API(Application Programming Interface). The English Numberbatch file is used to generate ConceptNet (Fig. 2) vectors. It consists of English language words, each associated with 300 floating point numbers based on their relationship with other words in the numberbatch. The words in the dataset are represented using a 300 dimensional vector and the vectors of all the words in a set of tweets of a particular individual are combined using component-wise summation. The TF-IDF vector was computed for each row. TF (Term Frequency) is the frequency of each word in a particular document. IDF (Inverse Document Frequency) is inverse of document frequency (frequency of documents containing a particular word). The TF-IDF score considers the frequency of words in a document, and also indicates the importance of a word in a document. The feature vector was obtained by combining TF-IDF, EmoSenticNet, LIWC and ConceptNet features. The size of feature vector was 1850. Using SVD(Singular Value Decomposition), the number of features was reduced to 50.

C. Training

Text classification is an important task in Supervised Machine Learning. The Naive Bayes classifier is the baseline in many studies[10]. It is very useful when there is limited memory. It is very fast to train and sometimes outperforms other classifiers. It provides many variations that can be used for different applications. Support Vector Machine (SVM) is similar to Logistic Regression. But it is very useful when the data is not linearly separable. It has been reported that SVM works best for text classification[11]. Text is converted into a suitable representation, and is fed into SVM. It works well when the dimensionality of the feature vector and the training data is very large. Neural Network[2] uses the processing of the brain as a basis to develop algorithms that can be used to mathematically model complex patterns and prediction problems.

The training module operates separately on the four classes of MBTI. Each class consists of two traits. These two traits are mapped to binary 0 or 1. TF-IDF feature vector is generated for the data. The text is then represented using TF-IDF, EmoSenticNet[3], ConceptNet and LIWC features. SVD is applied to reduce the size of feature vector[12] (from 1850 to 50 features). SVM is trained on the data. The parameters of SVM are adjusted to obtain probabilities of MBTI traits in the test data. Neural Network with softmax output was also trained on the data. The network consisted of three hidden layers with 200, 50 and 16 nodes respectively. The output layer consisted of 2 nodes. Naive Bayes classifier was also trained on the data. The accuracy of the three models was compared.

D. Testing and Validation

The new text is preprocessed using preprocessing module. The four pre-trained models corresponding to the four MBTI classes is loaded. Pre-trained SVD is applied to reduce the size of feature vector. The resultant feature vector is used to predict the probability or softmax output for the MBTI traits. The resultant MBTI type is also obtained (Table I, Fig. 1). A split ratio of 70:30 was maintained for the training and test data.

Tweets from a user (separated by |||)	MBTI type
my childhood was happy and filled with friends. as i grew up, i became distant and depressed. im getting better now. im actively trying to be less anti-social.||| my dad was drunk and a gambler, so my parents fought all the time. and my mom wanted me to be a cheerleader and do all these sports and be more social and it didnt want it and it was really stressful...	INTP

TABLE III
SAMPLE DATASET

E. Web Application Development

A Web Application was developed to provide a simple user interface to take the personality test. The web application allows text to be input for analysis, directly or by uploading a text file. The text is sent to the backend(to the pre-trained models). It is analysed, and the predicted personality scores are sent back to the frontend. Results are then displayed on the user interface, in a user-friendly and readable manner. The screenshots from the Web Application developed are shown in Fig. 4, and Fig. 5.

VIII. Results and Discussions

The goal of the proposed approach was to analyze and predict the personality traits of a person. A comparative study of various classifiers and feature vector combinations was done to obtain the most accurate prediction of the personality trait. A combination of feature vectors was used.

Feature Vector	I/E	S/N	T/F	J/P
TF-IDF	80.8%	88.1%	81.4%	74.9%
TF-IDF+LIWC	81.9%	87.5%	83.4%	76.3%
TF-IDF+LIWC(SVD)	85.3%	90.4%	85.7%	74.9%

TABLE IV
ACCURACIES WITH NEURAL NET CLASSIFIER

Feature Vector	I/E	S/N	T/F	J/P
TF-IDF	77.1%	86.2%	77.3%	62.1%
TF-IDF+LIWC	77.6%	86.7%	78.0%	61.0%
TF-IDF+LIWC(SVD)	77.8%	86.0%	75.6%	63.8%

TABLE V
ACCURACIES WITH NAIVE BAYES CLASSIFIER

Feature Vector	I/E	S/N	T/F	J/P
TF-IDF	73.9%	79.8%	84.3%	77.1%
TF-IDF+LIWC	85.0%	88.2%	86.1%	79.0%
TF-IDF+LIWC(SVD)	83.9%	87.9%	86.2%	78.0%

TABLE VI
ACCURACIES WITH SVM CLASSIFIER

The feature vector combination that gave the best accuracy with Neural Net classifier was LIWC and TF-IDF (Table IV), with feature reduction. The accuracy for S/N was 90.45%, indicating that it is easy to identify this class in the text over other classes. Naive Bayes classifier (Table V) reported best accuracy of 86.72% for S/N, without feature reduction. SVM (Table VI) also reported the best accuracy of 88.27% for S/N, without feature reduction (TF-IDF+LIWC features).

Classifier	E/I	S/N	T/F	J/P
Naive Bayes	77.0%	86.2%	77.9%	62.3%
SVM	**84.9%**	**88.4%**	**87.0%**	**78.8%**
Neural Net	77.0%	86.3%	54.1%	61.8%

TABLE VII
ACCURACIES WITH TF-IDF, LIWC, EMOLEX AND CONCEPTNET

The feature vector combination of LIWC and TF-IDF with feature reduction did not show significant improvement in results. The accuracy was not affected by the addition of Emolex. Using bigrams instead of unigrams decreased the accuracy.

It was observed that SVM outperformed other classifiers for all the MBTI classes (Table VII). For, I/E and S/N it was observed that SVM gave the best results for LIWC and TF-IDF feature vector combination without feature reduction. On addition of ConceptNet and EmoSenticNet features and reducing the number of features, it was observed that there was an improvement in the performance of SVM.

IX. Conclusion

The main aim of this work was to build a personality profile, using text written by the user. Preliminary analysis involved searching for patterns in sentiments and analysing distribution of emotions in the data.

The text was then preprocessed, by removing hyperlinks, numbers, punctuations, and context-sensitive words. Feature vectors were constructed using TF-IDF. Emolex, ConceptNet and LIWC features were also appended to the feature vector. After significant feature reduction, the feature vectors were used for training and testing machine learning models.

Different machine learning models, with different combinations of the feature vectors, were compared. For neural networks, it was observed that the best results were achieved after applying SVD, but accuracy was further improved on adding LIWC. Accuracy reduced when Emolex features were added to the feature vector. For Naive Bayes, best results were observed when LIWC and Emolex were added. Overall accuracy reduced on using SVD for Naive Bayes. The best accuracy was obtained from SVM with TF-IDF, Emolex, ConceptNet and LIWC feature vector combinations. The usefulness of the models with each feature vector in each MBTI class was tested.

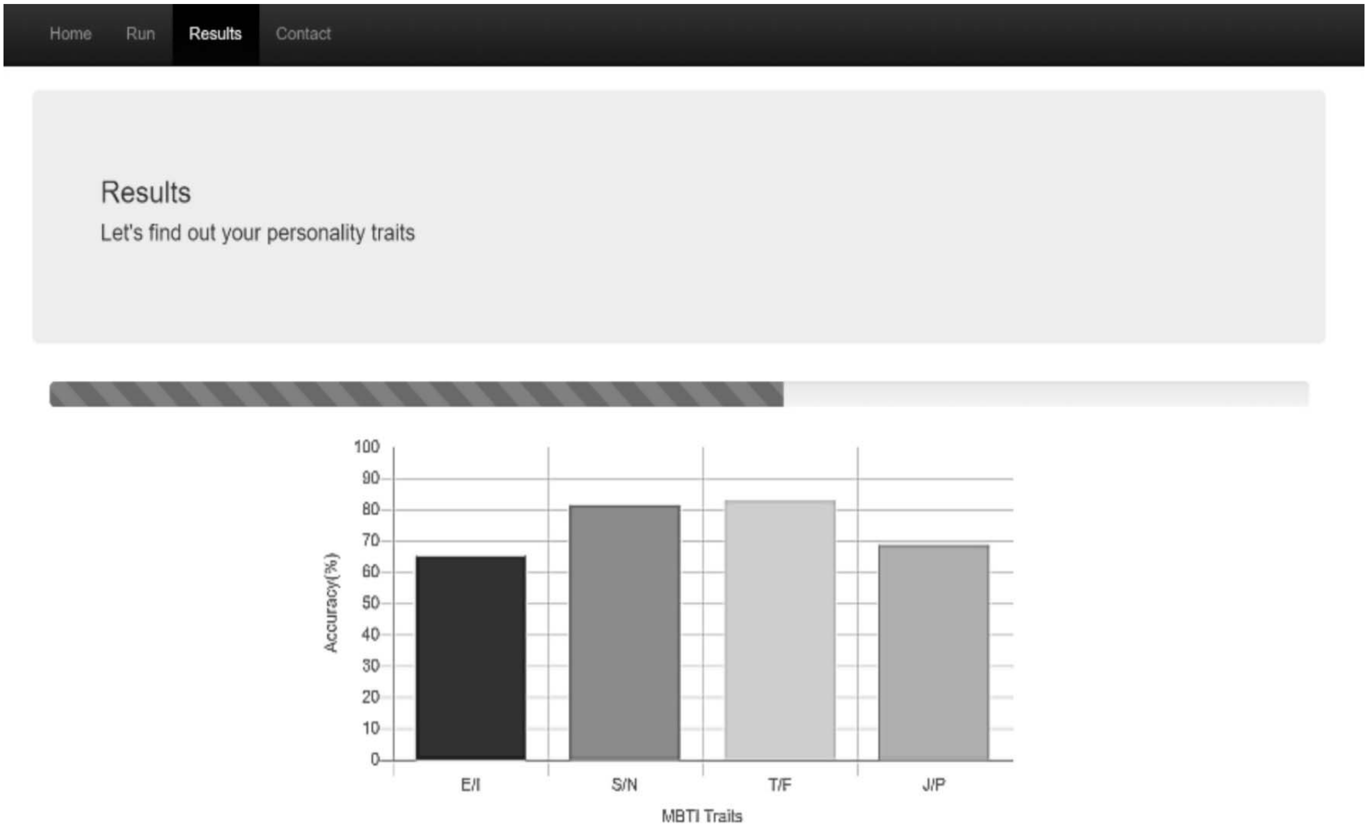

Fig. 4. After loading the text to be analysed, progress bar along with the accuracy of the classifier per iteration is shown.

Previously done work has achieved accuracy up to 63%[2], mainly for prediction of Big Five traits, while MBTI is a lesser explored personality scale. In this work, MBTI has been further explored, and an accuracy of up to 88% has been observed.

X. Future Work

Deeper analysis can be performed to find the intended meaning behind usage of words. Weightage can be given to the differences between words depending on their gravity, for example, the words "blue", "sad" and "melancholy" portray different intensities of depression and can make a huge difference during diagnosis.

Also, the way a word is spoken or enunciated also affects the intended meaning conveyed by a speaker[7]. Tone of voice and stressed points of a sentence, may make a difference in identifying hypotheticals and language features. Also, the same word said differently could indicate two different emotions identifiable from the word usage alone, and the distinction may be important for mood analysis. Analysis of the tone of voice by using recorded data of a person's speech would be a prime area to extend the work.

Acknowledgment

We would like to express our sincere thanks to Dr. Naren Rao and Dr. Sydney Moirangthem at the Department of Psychiatry, NIMHANS(National Institute of Mental Health and Neurosciences), for their guidance in understanding the psychological aspects of Persona Traits Identification.

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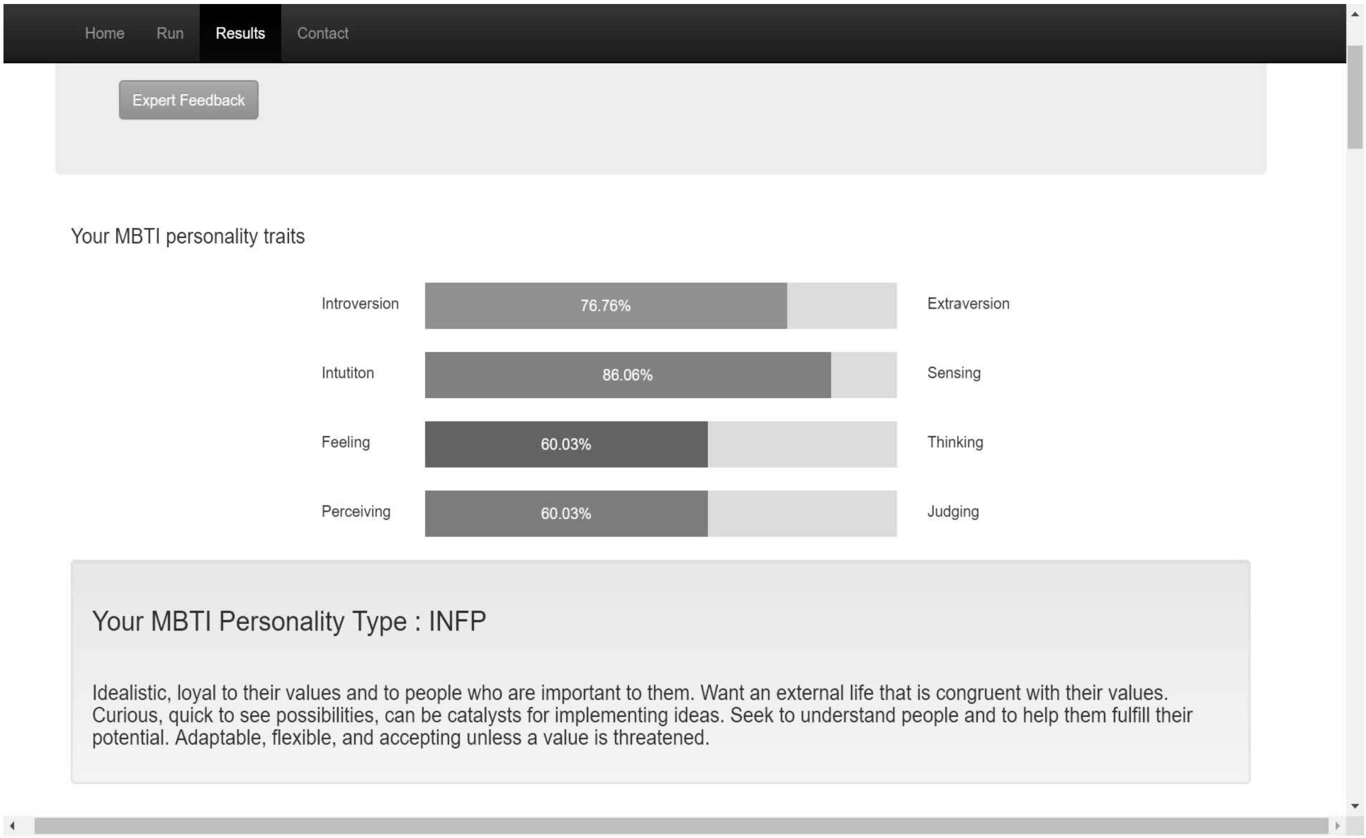

Fig. 5. MBTI scores for various MBTI classes and description of the MBTI type. There is an option to provide expert feedback that will be used for improving the models.

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