PERSONALITY ANALYSIS AND PREDICTION FROM BANGLA HANDWRITTEN TEXT DOCUMENTS

A PROJECT REPORT

submitted by

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Examination Roll No.: 2024161203

Registration No.: A01-1112-117-014-2021 of 2021-2022

Paper Code: CMSA DSE-VI

Semester: VI

in partial fulfillment of the requirements for the award of the Degree

of

Bachelor of Science (Honours)

in

Computer Science

under the supervision of

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Dept. of Computer Science

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April 2024

DECLARATION

I, Darpan Bhattacharya, Examination Roll No.: 2024161203, Registration No.: A01-1112-117-014-2021 of 2021-2022, student of B.Sc. (Hons.) in Computer Science, hereby declare that this project report titled **Personality Analysis and Prediction from Bangla Handwritten Text Documents** which is submitted by me to the Department of Computer Science, Ramakrishna Mission Vivekananda Centenary College, Rahara in partial fulfilment of the requirement for the award of degree of Bachelor of Science (Honours) is a presentation of my own original work and not copied from any other source without proper citation and has not been previously included in a project report / dissertation / thesis submitted to this or any other institution for a degree, diploma or any other qualification. The project work was done under the supervision of Dr. Chayan Halder.

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CERTIFICATE

I hereby certify that the project report titled **Personality Analysis and Prediction from Bangla Handwritten Text Documents** which is submitted by Darpan Bhattacharya, Examination Roll No.: 2024161203, Registration No.: A01-1112-117-014-2021 of 2021-2022, Department of Computer Science, Ramakrishna Mission Vivekananda Centenary College, Rahara in partial fulfilment of the requirement for the award of the degree of Bachelor of Science (Honours), is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any degree or diploma to this institution or elsewhere.

Date: Dr. Chayan Halder

(Project Supervisor)

Date: (External Examiner)

ACKNOWLEDGMENT

I would like to thank my project guide, Dr. Chayan Halder for helping and guiding me throughout the duration of the project, and for always patiently assisting me and providing valuable critical inputs whenever necessary.

I would also like to thank our respected principal, Swami Kamalasthananda maharaj, and our vice-principal and coordinator, Swami Vedanuragananda maharaj, for providing me with the opportunity to work on this project.

Finally, I would like to thank my family and friends for their continuous support.

Darpan Bhattacharya

ABSTRACT

Handwriting, also known as “brain writing” can be utilized as a rational strategy for understanding and gaining insight into various aspects of a individual, including their personality. Using handwriting as a tool to understand the personality traits of an individual has been traditionally done by expert graphologists. Using modern computer vision and image processing techniques, we can try to emulate the same work in a much more objective and precise manner. There have been multiple studies in English which aim to correlate various features of an individual’s handwriting with their personality traits. However there has been very few such studies in other languages. In this study, we analyze various structural and morphological features of an individual’s Bangla handwriting at document level, and utilize those features to predict the Big Five personality traits of that individual using different machine learning techniques.

CONTENTS

Chapter 1

INTRODUCTION

For centuries, handwriting has been used as a common form of communication and expression among humans. The nature of handwriting being unique to an individual's identity has led to studies that investigate the correlation between the handwriting of an individual and their personality traits. There have been various research papers showing the link between handwriting and the neurological aspects of humans, one such study being [1], where it was shown that the brain forms characters based on habits of writers and each neurological brain pattern forms a distinctive neuromuscular movement which is similar for individuals with the same type of personality. Thus we can say that from this perspective, handwriting is an accurate mirror of people's brain.

If there exists a system which can predict the personality traits of a person accurately enough, that may be helpful to remove the potential human bias associated with traditional big-five personality tests. In a traditional big-five test, the personality traits of a person are predicted based on their response to the questionnaire provided, thus the results are calculated based on feedback which can be voluntarily fabricated by untruthful responses. However, if the same test is done by analyzing the handwriting of the person, that bias can be minimized.

English has been the dominant language when it comes to personality traits analysis via handwriting. With approximately 280 million native speakers, Bangla is the sixth most spoken native language and the seventh most spoken language by the total number of speakers in the world. It is also the fifth most spoken Indo-European language. [2]

There are many regions in rural Bengal where Bangla is still the primary language used for both verbal and written communication. Having an automated system which can automatically analyze an individual's personality from their Bangla handwriting, may have practical utility in many fronts, medical and otherwise, especially in such places.

One of the main challenges for the Bangla langauge is the extremely limited information available both in and about the language on digital platforms. Thus it is quite difficult for obtaining information both in and about Bangla for practical usage, even in modern times. Because of its nature, the Bangla script contains features like conjunct characters, *matras* etc., which make techniques like line and character segmentation very difficult to execute. Besides that, processing handwritten Bangla text may also contain other properties like slant, skew, inconsistency, etc. which make processing such texts an even bigger challenge.

The objective of this project is to extract various structural and morphological features of an individual's Bangla handwriting using automated handcrafted feature extraction techniques at a document level, and then use the extracted features to predict the personality traits of the same individual using machine learning techniques.

The project report is structured as follows: related works are described in Chapter 2, details about the Big Five model are provided in Chapter 3, Chapter 4 contains details about the dataset used in our study, methodology and results are discussed in Chapters 5 and 6 respectively, and finally, conclusion and future scope is described in Chapter 7.

Chapter 2

LITERATURE REVIEW

Although there have been multiple studies conducted which correlate the personality analysis of an individual with their handwriting in English, besides [3] which uses various morphological and structural properties of Bangla characters to analyse different personality traits, there has been no other study so far which links Bangla handwriting to an individual's personality traits.

Gavrilescu and Vizireanu [4] proposed the first non-invasive three-layer architecture in literature based on neural networks that aimed to determine the Big Five personality traits of an individual by analyzing offline English handwriting. They obtained accuracies of 84.4% in intra-subject tests and 80.5% in inter-subject tests, obtaining around 84% accuracy for openness, extraversion and neuroticism traits, and around 77% for conscientiousness and agreeableness traits.

Ghosh et al. [5] carried out a study that extracted structural features, such as loops, slants, cursive, straight lines, stroke thickness, contour shapes, etc. from different zones of isolated English lowercase character images to derive a hypothesis based on a dictionary of graphological rules which had the ability to categorise the personal, positive, and negative social aspects of an individual.

Mukherjee and De [6] analyzed various characteristics of handwriting like size, spacing, slant, skew, pressure, etc. to examine the distinctiveness of handwriting based on the different characteristics.

Halder et al. [7] created a writer identification system in Bangla script. We have attempted to exploit the similar traits utilized by them in our work for personality identification.

Biswas et al. [3] created the only known study of personality analysis in Bangla so far using handwritten Bangla characters. While their work utilizes various structural and morphological features of handwriting at a character level, our work focuses doing so at a document level to then compare the extracted features with the Big Five personality traits of the same individuals.

Chapter 3

THE BIG FIVE MODEL

The Big Five personality traits, sometimes known as "the five-factor model of personality" or "OCEAN model", is a grouping of five unique characteristics used to study personality. It has been developed from the 1980s onward in psychological trait theory. [8]
The Big Five model consists of the following five personality traits:

- Openness
- Conscientiousness
- Extraversion
- Agreeableness
- Neuroticism

3.1 OPENNESS

Openness (also referred to as openness to experience) emphasizes imagination and insight the most out of all five personality traits. People who are high in openness tend to have a broad range of interests. They are curious about the world and other people and are eager to learn new things and enjoy new experiences.
People who are high in this personality trait also tend to be more adventurous

and creative. Conversely, people low in this personality trait are often much more traditional and may struggle with abstract thinking. [9]

3.2 CONSCIENTIOUSNESS

Among each of the personality traits, conscientiousness is one defined by high levels of thoughtfulness, good impulse control, and goal-directed behaviors. Highly conscientious people tend to be organized and mindful of details. They plan ahead, think about how their behavior affects others, and are mindful of deadlines.

Someone scoring lower in this primary personality trait is less structured and less organized. They may procrastinate to get things done, sometimes missing deadlines completely. [9]

3.3 EXTRAVERSION

Extraversion is a personality trait characterized by excitability, sociability, talkativeness, assertiveness, and high amounts of emotional expressiveness. People high in extraversion are outgoing and tend to gain energy in social situations. Being around others helps them feel energized and excited.

People who are low in this personality trait or introverted tend to be more reserved. They have less energy to expend in social settings and social events can feel draining. Introverts often require a period of solitude and quiet in order to "recharge." [9]

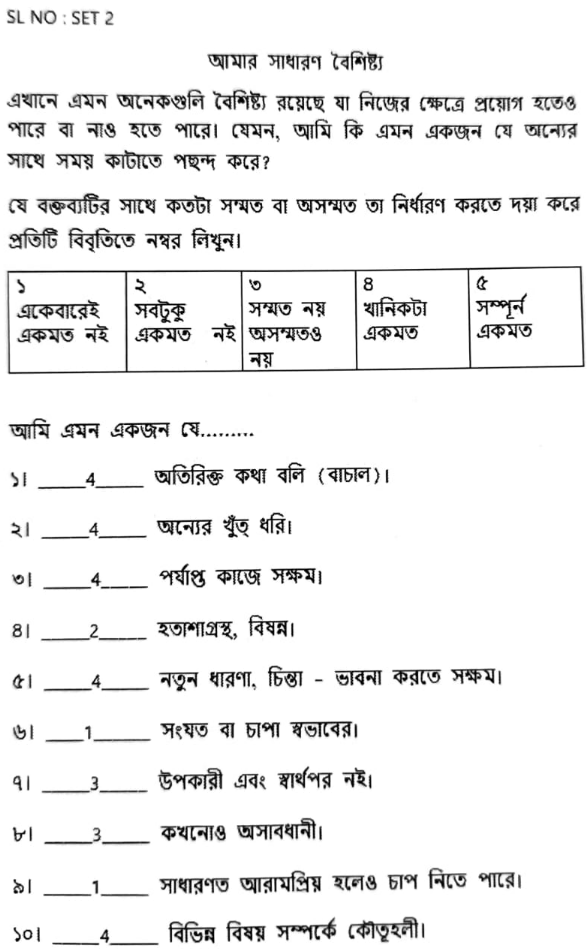
3.4 AGREEABLENESS

This personality trait includes attributes such as trust, altruism, kindness, affection, and other prosocial behaviors. People who are high in agreeableness tend to be more cooperative while those low in this personality trait tend to be more competitive and sometimes even manipulative. [9]

3.5 NEUROTICISM

Neuroticism is a personality trait characterized by sadness, moodiness, and emotional instability. Individuals who are high in neuroticism tend to experience mood swings, anxiety, irritability, and sadness. Those low in this personality trait tend to be more stable and emotionally resilient. [9]

Figure 3.1 shows a glimpse of the Big Five questionnaire provided to the individuals for their Big Five personality test.



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আমার সাধারণ বৈশিষ্ট্য

এখানে এমন অনেকগুলি বৈশিষ্ট্য রয়েছে যা নিজের ক্ষেত্রে প্রয়োগ হতেও পারে বা নাও হতে পারে। যেমন, আমি কি এমন একজন যে অন্যের সাথে সময় কাটাতে পছন্দ করে?

যে বক্তব্যটির সাথে কতটা সম্মত বা অসম্মত তা নির্ধারণ করতে দয়া করে প্রতিটি বিবৃতিতে নম্বর লিখুন।

১ একেবারেই একমত নই	২ সবটুকু একমত নই	৩ সম্মত নয় অসম্মতও নয়	৪ খানিকটা একমত	৫ সম্পূর্ন একমত

আমি এমন একজন যে.........

১। _____4_____ অতিরিক্ত কথা বলি (বাচাল)।

২। _____4_____ অন্যের খুঁত ধরি।

৩। _____4_____ পর্যাপ্ত কাজে সক্ষম।

৪। _____2_____ হতাশাগ্রস্থ, বিষন্ন।

৫। _____4_____ নতুন ধারণা, চিন্তা - ভাবনা করতে সক্ষম।

৬। ____1______ সংযত বা চাপা স্বভাবের।

৭। _____3_____ উপকারী এবং স্বার্থপর নই।

৮। _____3_____ কখনোও অসাবধানী।

৯। _____1_____ সাধারণত আরামপ্রিয় হলেও চাপ নিতে পারে।

১০। _____4_____ বিভিন্ন বিষয় সম্পর্কে কৌতূহলী।

Figure 3.1: A page from the Big Five personality test questionnaire

Chapter 4

DATASET

There are very few public handwritten datasets available for the Bangla script. For this study, we not only need the Bangla handwriting of the individual, but we also simultaneously need their big-five data for their personality analysis. We utilized the Bangla handwritten dataset used by Halder et al. [7] and the big-five dataset collected by Biswas et al. [3] of the same individuals for our purpose. Since our work uses a document-level approach, we used the portion of the handwritten dataset used by Halder et al. [7] which contained both guided and unguided handwriting from 20 individuals, both male and female, in the age range of 14 to 60 years. For each individual, we utilized 13 data forms of guided handwriting where the individual had to hand-write the given text, and 1 data form of unrestricted handwriting where the individual was allowed to hand-write any text of their choice. Thus, the Bangla handwritten dataset utilized by us consisted a total of $22 \times 14 = 308$ sheets of Bangla handwritten data. An example of a data form utilized by us which contains guided handwriting is given in Figure 4.1 and an example of a data form utilized by us which contains unrestricted handwriting is given in Figure 4.2.

The big-five test of the individuals contained 44 close-ended and scaled questions, each of which could be answered in a scale from 1 to 5, 1 signifying strong disagreement and 5 signifying strong agreement, from which their big-five score was calculated for each of the openness, conscientiousness, extraversion, agreeableness and neuroticism traits.

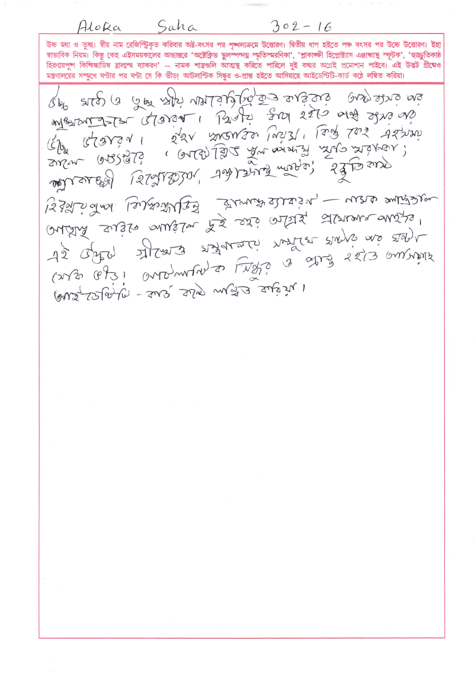

Figure 4.1: An example of a data collection form containing guided handwriting

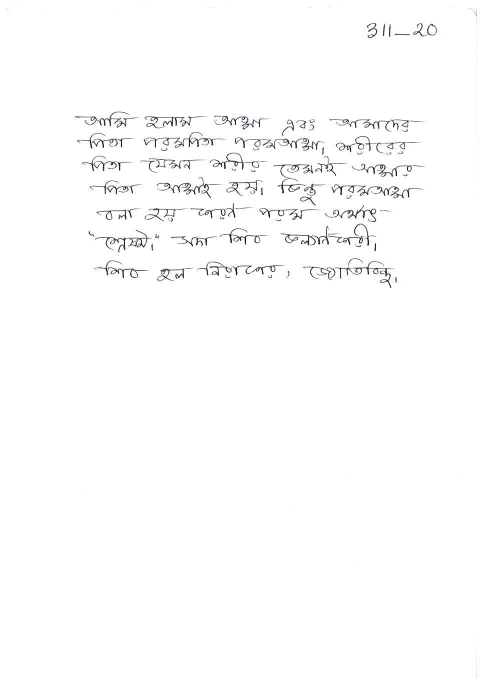

Figure 4.2: An example of a data collection form containing unrestricted handwriting

Chapter 5

METHODOLOGY

There have been various studies that show a relation between the handwriting of an individual and their personality traits. Plamondon [1] showed that the brain forms characters based on habits of writers and each neurological brain pattern forms a distinctive neuromuscular movement which is similar for individuals with the same type of personality. Gowda et al. [10] showed that there are no significant and concrete differences between the psychodiagnostic assessment of personality through Children's Personality Questionnaire (CPQ) and handwriting analysis.

In this study, we extract various morphological and structural features of an individual's Bangla handwriting, and then used machine learning techniques to observe a correlation between the features obtained from their handwriting and their personality traits. Figure 5.1 shows a flowchart demonstrating the workflow of our framework.

5.1 EXTRACTING THE HANDWRITTEN PORTION TO BE ANALYZED

Firstly, we separated the handwritten part from the data collection form. We did that by removing all red segments from the form and using masking technique. Since all the printed portion in a blank data collection form was in red, by removing the red colour, we were able to obtain only the handwritten portion of the form. For the forms containing unrestricted handwriting, this step was

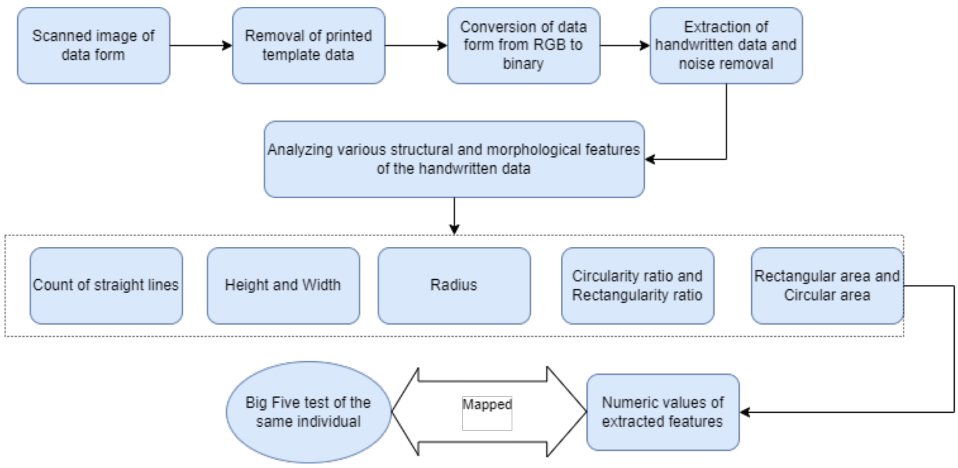

Figure 5.1: Flowchart demonstrating the workflow of our framework

redundant since the data form containing unrestricted handwriting is initially blank.

Then we separated the main written portion in the form, from other accessory details of the writer. We did that by performing erosion and dilation on the form so that the written portions got merged into components. Since the accessory details were pretty small compared to the main written portion, we extracted the largest component from the obtained components, which gave us the main handwritten portion to be analyzed.

5.2 FEATURE EXTRACTION

Once we had the main handwritten part of the forms, we tried to extract various structural and morphological features for analysis.

5.2.1 Straightness (S)

Here we tried to analyze the horizontal straightness of the handwriting. We did that by running a small horizontal mask over the entire handwritten data, and counting the number of significant overlaps with the mask in the data.

5.2.2 Height (H) and Width (W)

We calculated the median height and width of each data form. We did that by computing the height and width of each connected component of the handwriting and then computing their median. Extremely small connected components were discarded as noise.

5.2.3 Radius (R)

We calculated the median radius of each data form. We did that by computing the minimum radius that could enclose a connected component for each connected component and then computed their median. Extremely small connected components were discarded as noise.

5.2.4 Rectangularity Ratio (RR)

We calculated the rectangularity ratio (RR) of each component by computing the area of the smallest rectangle that enclosed a component and then dividing the contour area of that particular component by the area of the smallest rectangle enclosing the component. Figure 5.2 demonstrates a visual example of a data form where rectangles are drawn (in blue) over the contours (in green).

$$RR = \frac{\text{Contour area of a particular component}}{\text{Area of the smallest rectangle enclosing the component}}$$

5.2.5 Circularity Ratio (CR)

We calculated the circularity ratio (CR) of each component by computing the area of the smallest circle that encloses a component and then dividing the contour area of that particular component by the area of the smallest circle enclosing the component. Figure 5.3 demonstrates a visual example of a data form where circles are drawn (in red) over the contours (in green).

$$CR = \frac{\text{Contour area of a particular component}}{\text{Area of the smallest circle enclosing the component}}$$

5.2.6 Rectangular Area (RA)

We calculated the rectangular area (RA) by computing the area of the rectangle formed by the median height (H) and the median width (W) of the components.

$$RA = H \cdot W$$

5.2.7 Circular Area (CA)

We calculated the circular area (CA) by computing the area of the circle formed by the median radius (R) of the components.

$$CA = \pi \cdot R^2$$

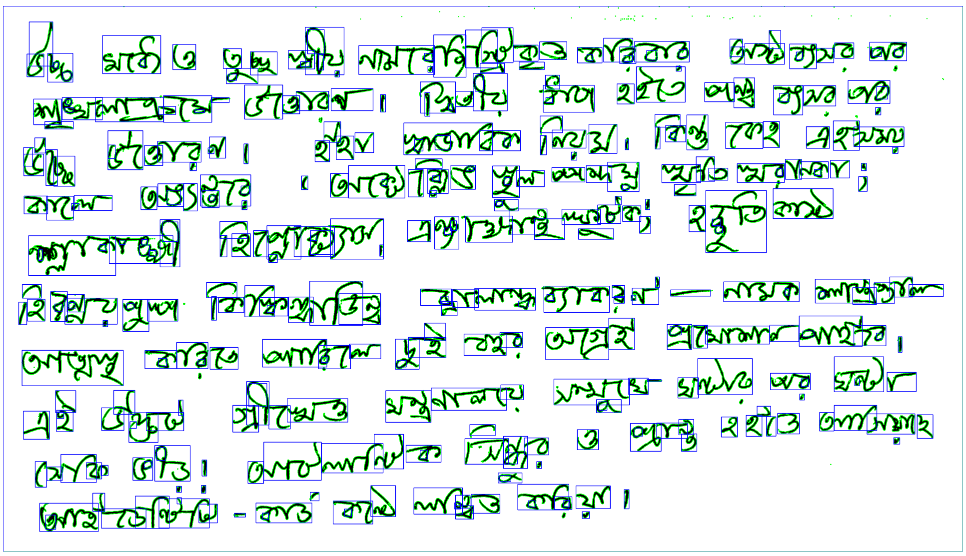

Figure 5.2: Rectangles drawn over components

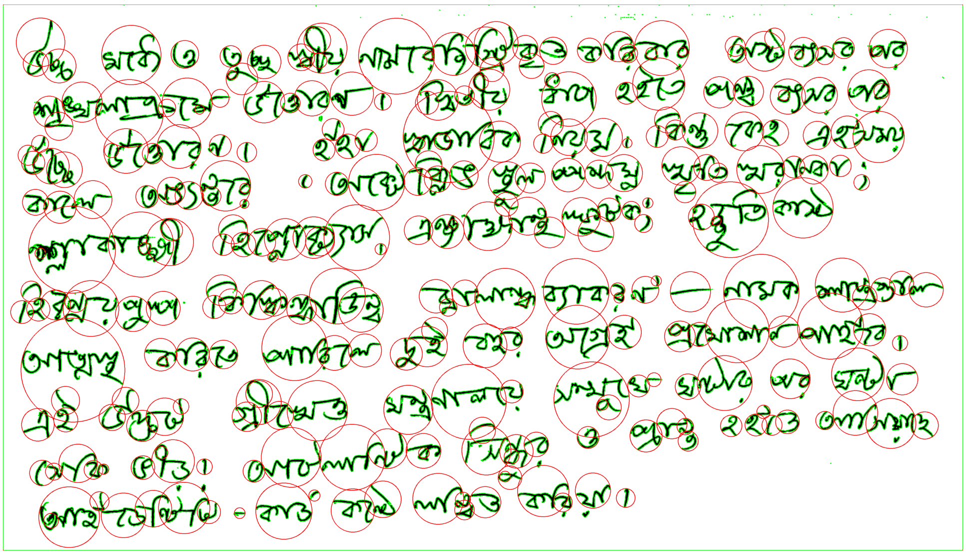

Figure 5.3: Circles drawn over components

TOOLS USED

We used Python3 on the VSCode text editor for our work, on a computer with Windows 11 Home Operating System and 11^{th} Gen Intel(R) Core(TM) i5-1155G7 2.50GHz processor. The computer had 8 GB of RAM and a 64-bit operating system.

We used the Random Forest Regressor from the skicit-learn module [11] for our work. We used the `sklearn.ensemble.RandomForestRegressor` [12] and `sklearn.multioutput.MultiOutputRegressor` [13] models for predicting the Big Five values. We utilized the 'stratify' attribute for effectively splitting our dataset into proper testing and training data.

5.3 REGRESSION ANALYSIS

Regression analysis is suitable where it needs to be determined which factor is more important, and which variable has more impact on the whole scenario. In the current study, the impact of the extracted features from the handwriting on the analysis of personality traits is of major importance. We used the Random Forest Regressor from the skicit-learn module [11] for our purpose. We split our dataset into training and testing sets in a 70:30 ratio.

In the Big Five personality test that was conducted, each individual obtained a score out of 44 for each personality trait. For our Random Forest Regressor model, we normalized the data for each personality trait by using the following formula:

$$NS_{i,t} = \frac{S_{i,t} - \min_t}{\max_t - \min_t}$$

where $NS_{i,t}$ denotes the Normalized Score of the i^{th} individual for the t^{th} personality trait, $S_{i,t}$ denotes the Normalized Score of the i^{th} individual for the t^{th} personality trait, and $\min_t$ and $\max_t$ denote the minimum and maximum scores obtained by any individual for the t personality trait respectively.

Chapter 6

RESULTS & ANALYSIS

We tested our work on data samples collected from 22 different individuals in the age range of 14-60 years, from different spheres of life. Each individual had a total of 14 data forms consisting of their Bangla handwriting, which were distributed in the ratio of 10:4 for our training and testing sets respectively. Thus, we utilized a total of $22 \times 10 = 220$ training data forms and $22 \times 4 = 88$ testing data forms for our study. Additionally, each individual had their Big Five test taken, where they answered 44 questions, each in a range from 1 to 5, 1 indicating strong disagreement and 5 indicating strong agreement. We normalized the Big Five scores, using the formula given in section 5.3 of this report, and trained and tested our model on the normalized data.

The Root Mean Square Error (RMSE) is used as the measure for estimation of the prediction quality. Since we had already normalized the Big Five data before using it for training or testing, our Root Mean Squared Error is thus normalized too, and is equivalent to the Normalized Root Mean Sqaured Error (NRMSE).

We obtained an **RMSE of approximately** 0.15 **(**±0.005**) for prediction on the entire data set**, both for the RandomForestRegressor and MultiOutputRegressor models. Table 6.1 gives the RMSE distributions for the different personality traits, with an adjustment of approximately ±0.005 for different executions. From Table 6.1, we can observe that all the personality traits have quite satisfactory RMSE values, given that our worst-case RMSE for any personality trait is 0.1894 according to the RandomForestRegressor and 0.1921 according the MultiOutputRegressor for the Agreeableness personality trait. We obtained the best RMSE for the Openness personality trait, which had a RMSE of 0.1132 according to the RandomForestRegressor, and a RMSE of 0.1227 according to the MultiOutputRegressor. Overall, we obtained quite satisfactory average RMSE values: 0.1506 according to the RandomForestRegressor and 0.1582 according to the MultiOutputRegressor models.

Trait	**RandomForestRegressor**	**MultiOutputRegressor**
Openness	0.1132	0.1227
Conscientiousness	0.1490	0.1550
Extraversion	0.1334	0.1548
Agreeableness	0.1894	0.1921
Neuroticism	0.1678	0.1665
Average	**0.1506**	**0.1582**

Table 6.1: RMSE distributions of the different personality traits

6.1 COMPARATIVE ANALYSIS

Besides Biswas et al. [3], who performed a similar study but on character level, not document level, and obtained the best RMSE score of 3.11 by the Random Forest model for the Neuroticism trait, and the lowest average RMSE score of 3.83 by the Random Forest model, no other comparative study could be performed on the results because there have been no similar studies conducted on the Bangla language so far to the best of our knowledge.

6.2 VISUAL REPRESENTATIONS

We have provided charts which depict the comparison between the original values and the predicted values. For the sake of visual clarity, we have provided comparisons for 15 randomly picked data samples from the dataset.

Figure 6.1 depicts the original versus predicted values for the Openness personality trait. We can observe that most of the predicted values are quite close to the original value, with samples like sample 5 and sample 13 predicting almost the exact value. Figure 6.2 depicts the original versus predicted values for the Conscientiousness personality trait. Like the openness personality trait, here too we can see that most predicted values are quite close to the original values, with samples 7 and 8 almost predicting the exact value itself. However there exists few anomalies like samples 3 and 13, where the predicted values are not close to the original values. Similarly figures 6.3, 6.4 and 6.5 depict the original versus predicted values for the Extraversion, Agreeableness and Neuroticism personality traits, respectively. Overall, we can observe that barring few anomalies, the predicted values are quite close to the original values for the vast majority of the dataset.

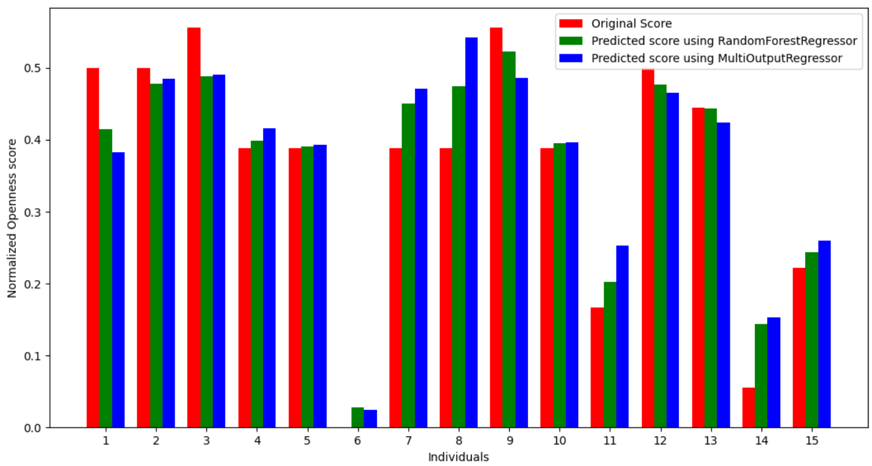

Figure 6.1: Original v/s predicted values for Openness personality trait

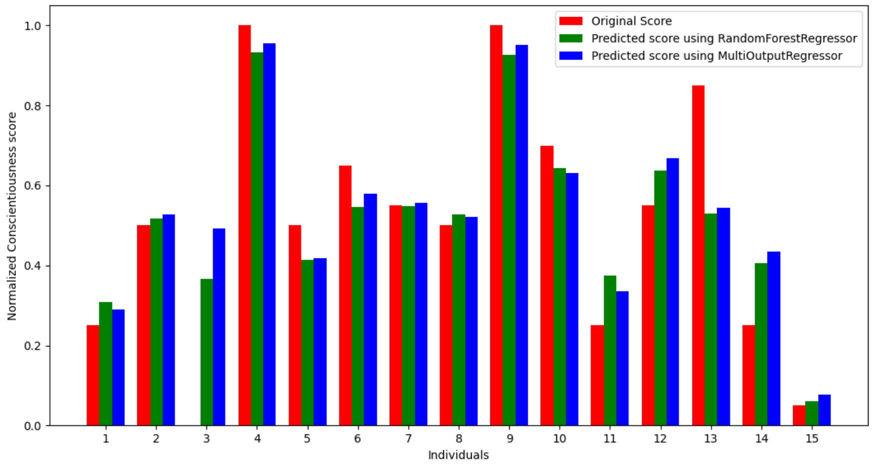

Figure 6.2: Original v/s predicted values for Conscientiousness personality trait

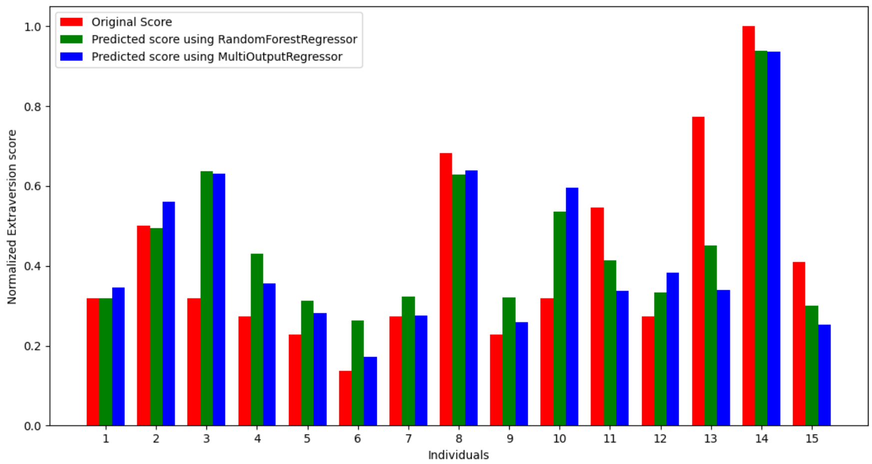

Figure 6.3: Original v/s predicted values for Extraversion personality trait

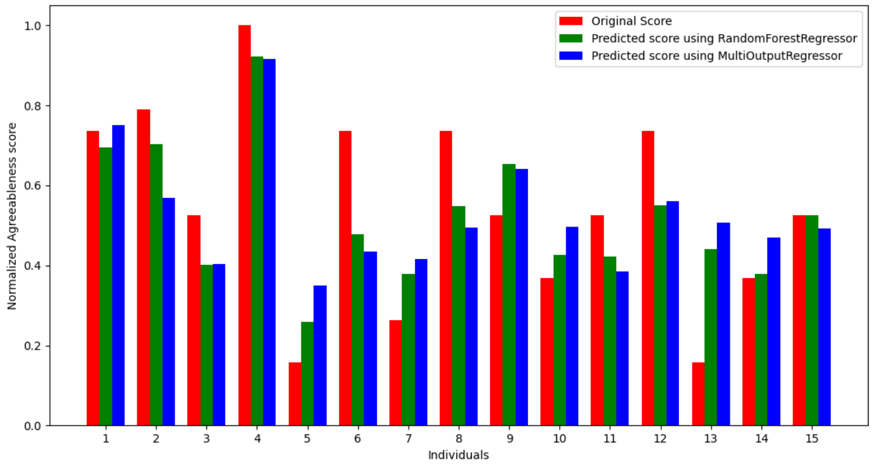

Figure 6.4: Original v/s predicted values for Agreeableness personality trait

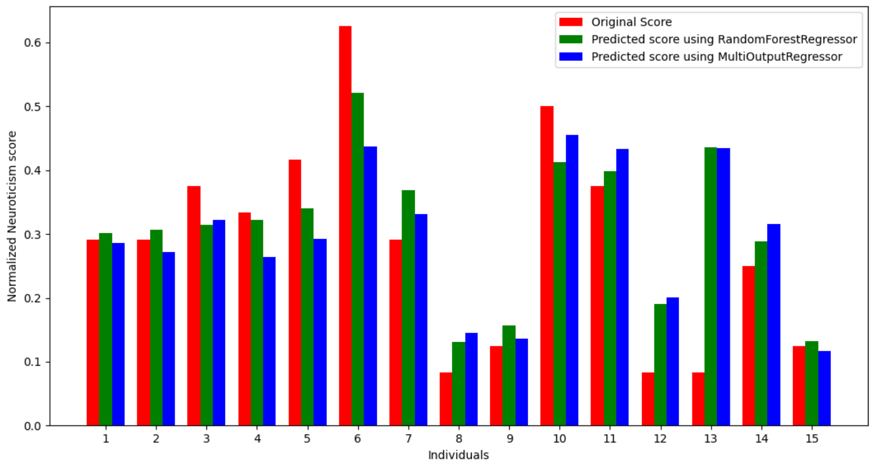

Figure 6.5: Original v/s predicted values for Neuroticism personality trait

Chapter 7

CONCLUSION & FUTURE SCOPE

From our results, we can conclude that analyzing Bangla handwriting on a document level can be quite satisfactorily compared with their Big Five personality traits. In our work, we utilized different structural and morphological features from the Bangla handwriting of 22 different individuals at a document level and compared it with their personality traits. Our results show that our methods are quite promising and have a very high potential of being used in real-life situations to identify an individual's personality traits from their handwriting.

One of the major issues that we faced in our work was the lack of more data samples. In future, the amount of data samples that are analyzed should be significantly increased for providing a much more accurate picture of the correlation between handwriting and Big Five personality traits. Various other structural and morphological features besides the ones that we have worked on can be utilized too. Line and character segmentation can be done on the handwritten data to provide better and more precise morphological features for analysis. The data can be tested on various other regressor models to obtain more precise results. Our study can also be extended to various other languages as well.

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