AI-BASED HANDWRITING ANALYSIS

NABIL SYAZANI BIN MOHD NASIR

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

AI-BASED HANDWRITING ANALYSIS WEB APPLICATION

NABIL SYAZANI BIN MOHD NASIR

This report is submitted in partial fulfillment of the requirements for the Bachelor of Computer Science (Artificial Intelligence) with Honours.

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

I hereby declare that this project report entitled

AI-BASED HANDWRITING ANALYSIS WEB APPLICATION

is written by me and is my own effort and that no part has been plagiarized without citations.

STUDENT : _____ Date: 11/9/2024

(NABIL SYAZANI BIN MOHD NASIR)

I hereby declare that I have read this project report and found this project report is sufficient in term of the scope and quality for the award of Bachelor of Computer Science (Artificial Intelligence) with Honours.

SUPERVISOR : _____ Date: 11/9/2024

(DR. NOOR FAZILLA BINTI ABD YUSOF)

DEDICATION

This final year project is dedicated to my PSM 1 supervisor, Dr. Noor Fazilla binti Abd Yusof, whose patience, guidance, and unwavering support have been instrumental throughout the journey of this project. Her dedication and consistent assistance have been invaluable, and I deeply appreciate her efforts and belief in my capabilities. I also dedicate this work to the domain expert from Medipro Venture Sdn. Bhd., whose collaboration and insights have significantly enriched the project.

Furthermore, I dedicate this project to my family, whose love, encouragement, and unwavering support have been my greatest source of strength. Their belief in me has been a constant motivation throughout this project establishment.

Last but not least, I want to thank me. I want to thank me for believing in me, I want to thank me for doing this all hard work. I want to thank me for having no days off. I want to thank me for never quitting. I want to thank me for always being a giver and trying to give more than I receive. I want to thank me for trying to do more right than wrong. I want to thank me for being me at all times.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my highest gratitude to several individuals and organizations for being a crucial part of my journey throughout my Final Year Project. I wish to start by mentioning my deep appreciation to my supervisor, Dr. Noor Fazilla Binti Abd Yusof, for her patience, guidance, and motivation throughout the project's completion. Her insightful contributions, comments, and eye-opening suggestions have significantly enhanced the quality of my work. The time we spent in meetings always resulted in practical and applicable improvements. I could not have completed this project as successfully without her support and expertise.

I would also like to express my heartfelt gratitude to my family especially my parents for providing me with unwavering emotional support. Their encouragement has been a constant source of strength, motivating me to keep going and stay strong throughout this journey.

Additionally, I extend my sincere thanks to Norhazifa, for the continuous support, feedback, and encouragement. The companionship and assistance have been invaluable, and I am grateful for her help in overcoming challenges and staying focused on my goals.

Lastly, I would like to thank Medipro Venture Sdn. Bhd. and their domain expert for the collaboration and support, which has been integral to the success of this project. Their contributions have provided real-world insights and practical applications for my work. Thank you all for your support and belief in my abilities.

ABSTRACT

The project, "AI-Based Handwriting Analysis," aims to transform the field of handwriting analysis through the utilization of artificial intelligence. This web-based application is designed to automatically analyse handwriting features from uploaded images and deduce the personality traits of the writer. The system addresses the inefficiencies and subjectivity inherent in manual handwriting analysis conducted by graphologists. Graphologists have traditionally conducted manual analysis throughout the years, which is time-consuming for obtaining handwriting features and personality traits from a single document. Moreover, manual analysis by different graphologists can lead to a conflicting opinion and ambiguous results of prediction. A domain expert from Medipro Venture Sdn. Bhd., who traditionally performs these analysis, will greatly benefit from this automated solution, promising immediate and consistent results. The application harnesses advanced AI techniques, including machine learning, computer vision, and image recognition, to accurately assess handwriting features. This project was done using the Agile Method to keep the progress on track. The result is the process of identifying key graphology features (baseline angle, top margin, slant angle, letter size, pen pressure, word spacing, line spacing) and accurately predicting personality traits such as emotional stability, mental energy, modesty, non-communicativeness, lack of discipline, poor concentration and social isolation. The project ultimately strives to identify graphology features in handwriting using computer vision techniques, build a machine learning-based analysis model for handwriting and develop an AI-Driven web app for handwriting analysis. By leveraging computer vision and machine learning techniques, the application streamlines handwriting analysis, providing consistent and efficient results that surpass manual methods. The aim is toward institutions seeking reliable personality evaluations, this AI solution will enhance accuracy and save time while offering valuable insights into individuals' characteristics.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

FYP	**-Final Year Project**
ANN	**-Artificial Neural Network**
AUC-ROC	**- Area Under the ROC Curve**
ROC	**-Receiver Operating characteristic Curve**
CNN	**-Convolutional Neural Networks**
CSCI	**-Computational Science and Computational Intelligence**
GANs	**-Generative Adversarial Networks**
IS	**-Intelligent Systems**
KNN	**-K-Nearest Neighbours**
MBTI	**-Myers-Briggs Type Indicator**
MFCCs	**-Mel-frequency Cepstral Coefficients**
ML	**-Machine Learning**
OCEAN	**-Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism**
RAM	**-Random Access Memory**
SGAN	**-Semi-supervised Generative Adversarial Network**
SVM	**-Support Vector Machines**
UX	**-User Experience**

LIST OF ATTACHMENTS

CHAPTER 1: INTRODUCTION

1.1 Introduction

Initially, handwriting is one of the most valuable ways to learn about a person's physical, mental, and emotional states out of all their distinctive personal qualities or in simple words, their personality traits. Handwriting is actually can be a helpful tool for determining a person's distinctive personality traits. In this case study, a collaboration will be made with the graphologist. Graphologists, or handwriting analysts, can analyse a person's handwriting to infer their personality. Since an analyst's accuracy greatly depends on his skill set, automated handwriting analysis can be used to correctly assess a person's personality. Hence, a web application with a handwriting analyser will be developed to ease the process.

The goal of this project is to employ the power of handwriting as a tool for understanding an individual's physical, mental, and emotional states, leading to unique personality traits. Working alongside expert graphologists who use handwriting analysis to deduce personality traits, this study proposes a web application that uses a handwriting analyser to streamline and enhance this process. The project's objectives are to identify personality traits and analyze handwriting styles to verify the handwriting features. The modules for this project include an interactive user interface, a handwriting analyser, and personality trait recognition. The target audience is institutions or departments looking for a way to evaluate individuals' characteristics and emotional well-being. The expected results are a dependable AI-based web application for handwriting analysis with high accuracy, an increase in efficiency over manual analysis, and valuable insights from the analysis results. Ultimately, this project strives to provide a solution that simplifies the assessment of personality traits through automated handwriting analysis, which can benefit institutions across various domains.

1.2 Problem Statement

Achieving accurate analysis with AI systems presents several significant challenges. One major difficulty is enabling computer vision to accurately interpret personality traits from handwriting patterns. This task requires the AI to understand the varieties of patterns in handwriting that correlate with different personality characteristics. Since there is no handwriting analysis system exist yet, graphologists have been doing manual analysis throughout the years, which is time-consuming to obtain the result of handwriting features and personality traits from a single handwriting document. Moreover, manual analysis by different graphologists can lead to a conflicting opinion and ambiguous results of prediction. Hence, this issue can lead to a bias in certain handwriting. Additionally, figuring out the emotional states of individuals from their handwriting adds another layer of complexity. This involves sophisticated analysis capabilities to accurately read and interpret the emotional state conveyed through various handwriting features.

1.3 Objectives

This project embarks on the following objectives:

1. To identify graphology features in handwriting using computer vision techniques.
2. To build a machine learning-based analysis model for handwriting.
3. To develop an AI-Driven web app for handwriting analysis.

1.4 Scope

There are three modules to be developed:

i. Interactive User Interface. In this module, the system displays a user interface that is easy to use for the user in the responsive web application.
ii. Handwriting analyser. In this module, the user can upload any handwriting documents for the system to read and analyse the features of the handwriting.
iii. Personality Traits Recognition. In this module, the module gives the list of personality traits that are matching with the handwriting.

Our main target user is a graphology company, Medipro Ventures Sdn. Bhd, that actively working on the process of assessing a person's characteristics and emotional well-being based on handwriting. In addition, a graphologist, the domain expert from the company mentioned is also the main target user to utilise the system for enhancing her work rate.

1.5 Project Significance

The significance of this project is that the system is capable to analyse varieties of handwriting documents with various handwriting features. This can be accomplished by uploading the documents to obtain the features and matching personality traits of a person, which benefits the graphologist to ease the process of analysing handwriting instead of doing it manually. This project is significantly crucial for the domain expert since it can assist her in analysing handwriting with ease instead of doing it manually which is time-consuming.

1.6 Expected Output

The reliable AI-Driven web application for handwriting analysis is designed to thoroughly analyse handwriting in order to accurately detect personality traits that has been decided to be implemented into the system. The personality traits are Emotional Stability, Mental Energy, Modesty, Lack of Discipline, Poor Concentration, Non-Communicativeness, and Social Isolation. In addition, this project's goal is to enhance the efficiency of analysis compared to manual methods used by some graphologists, while also providing valuable insights derived from the results of the handwriting analysis.

1.7 Conclusion

In conclusion, this project aims to overcome the challenges associated with achieving precise handwriting analysis by utilising AI techniques. It involves the creation of an AI-Driven web application that can interpret personality traits based on handwriting patterns. The main goals include standardizing results among graphologists, removing biases, and improving work efficiency through a user-friendly interface. The system is intended for Medipro Ventures Sdn. Bhd and their domain expert, which will include modules for user interaction, handwriting analysis, and recognition of personality traits. By automating the analysis process, the project seeks to save time and deliver consistent, trustworthy results, ultimately enhancing the accuracy and efficiency of handwriting-based personality assessments.

CHAPTER 2: LITERATURE REVIEW AND PROJECT METHODOLOGY

2.1 Introduction

This study of the literature will critically look at the body of knowledge regarding the field of handwriting analysis that has undergone significant developments due to advancements in artificial intelligence (AI) and machine learning (ML). Traditional graphology methods, which heavily relied on human interpretation of handwriting features, have been supplemented and, in some instances, supplanted by automated techniques harnessing the power of AI. This literature review presents a comprehensive overview of the latest methodologies in AI-based handwriting analysis, laying the groundwork for the project methodology that employs the Agile Methodology approach.

Handwriting analysis for personality prediction is a prominent area of research, as evidenced by multiple studies. For instance, one study utilised convolutional neural networks (CNNs) to extract features from handwriting samples and predict personality traits, demonstrating the potential of deep learning techniques in this domain. The authors of this study highlighted the effectiveness of CNNs in capturing subtle handwriting features, noting that features such as slant, baseline, pen pressure, and letter design are critical in determining personality traits (Sharma, 2022).

In this case study, there are six (6) handwriting features that can be extracted by the system which are Top Margin, Letter Size, Line Spacing, Word Spacing, Pen Pressure and Slant. In addition, for the personality traits, there are eight (8) of it which includes emotional stability, mental energy or willpower, modesty, personal harmony and flexibility, lack of discipline, poor concentration, non-communicativeness and lastly social isolation.

Another significant contribution to the field is the comparative study on handwriting-based personality prediction, which employed a semi-supervised generative adversarial network (SGAN). This study emphasised the value of integrating labelled and unlabelled data to improve classification performance. The authors stated, SGAN architecture utilizes both labelled and unlabelled data to train the classifier, which helps in generalizing well on the testing set (Zahid, 2022). This approach not only enhances the robustness of the model but also addresses the challenge of limited labelled data.

In addition, studies on recognising emotions from handwritten and drawn samples through the use of feature fusion methods have given us a better understanding of the wider applications of handwriting analysis. This particular research employed a blend of time-domain, ductus-based characteristics, and Mel-frequency cepstral coefficients (MFCCs) in order to build a decision support system for identifying emotional states. The researchers concluded that by extracting and combining various features from handwriting and drawing tasks, it is possible to effectively capture the emotional state of individuals (Nguyen, 2021).

The methodology for this project follows the Agile Methodology framework, which ensures a systematic and structured approach to developing the AI-based handwriting analysis system.

This project aims to develop a robust AI-based system for handwriting analysis by integrating findings from various studies and following the Agile Method approach. The system will use advanced AI techniques which include computer vision and template matching to analyse handwriting samples and offer insights into personality traits and emotional states. This literature review not only highlights existing methodologies but also lays the groundwork for the methodological approach used in this project.

2.2 Facts and Findings

In this section, we will focus on the project's domain, providing insights into its core value and outlining how it can contribute to the successful completion of the project.

2.2.1 Domain

The domain of this project is Computational Psychology with a focus on AI-Based Handwriting Analysis. This interdisciplinary field merges principles from psychology, artificial intelligence (AI), and computer science to develop systems capable of interpreting human handwriting for various psychological and personality assessments. The goal is to create a bridge between traditional handwriting analysis methods and modern computational techniques, offering more empirical and objective insights.

Handwriting Analysis, also known as graphology, studies handwriting to understand the writer's characteristics. Graphologists have historically examined handwriting size, slant, and pressure to make conclusions about the writer's personality, emotions, and psychological state. While its scientific credibility is a topic of debate, contemporary computational techniques are aiming to introduce greater precision to the field of handwriting analysis. For example, a study using convolutional neural networks (CNNs) has shown the potential of deep learning techniques in analysing handwriting, indicating that deep learning methods can accurately capture and interpret subtle handwriting features (Sharma, 2022). This project aims to use AI and machine learning to automate and improve handwriting interpretation. AI helps create intelligent systems that can learn from and interpret complex handwriting patterns. Machine learning techniques like CNNs and Generative Adversarial Networks (GANs) can extract detailed features from handwriting samples that are often hard for human analysts to perceive.

In addition, Computational Psychology involves using computational methods and models to understand and predict psychological phenomena. By integrating AI

with psychological theories, this project aims to create models that can predict personality traits and emotional states from handwriting samples. This represents a significant step towards quantifying and providing the insights traditionally garnered through more subjective graphological analysis. Personality prediction often involves assessing traits such as Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, commonly referred to as the Big Five personality traits (OCEAN). Emotional state prediction seeks to determine the writer's current emotions, such as happiness, sadness, or anxiety, based on specific handwriting features. Research on identifying emotional states found that combining time-domain and frequency-domain features provides a comprehensive understanding of the writer's emotional state (Nguyen, 2021).

Therefore, by situating the project within these domains, the research aims to bridge the gap between traditional handwriting analysis and modern AI techniques, providing more objective, reliable, and scalable methods for personality and emotional state assessment. This not only advances the field of computational psychology but also offers practical applications in areas such as psychological diagnostics, human resources, and personal development.

2.2.2 Existing System

The foundation for knowledge was established by significant research on the subject when the studies are among the methodological issues raised by the literature that is similar to the ongoing project which is the paper by (Samsuryadi et al., 2023), the framework developed in their research article combines image processing and machine learning methods to predict personality traits through handwriting analysis.

The project described in the research article operates at the intersection of psychology, graphology, machine learning, and image processing. This interdisciplinary domain involves leveraging advanced technological tools to analyse handwriting and uncover personality traits. By combining principles from psychology with cutting-edge machine learning algorithms and image processing

techniques, the project aims to provide a novel approach to understanding human behaviour through handwriting analysis.

The approach outlined in the research article involves the development of a framework that integrates image processing and machine learning methods to extract handwriting features and classify them according to the Big Five personality model. Past studies have demonstrated varying levels of accuracy in personality trait prediction, with some achieving high classification rates using techniques like support vector machines (SVM) and deep learning architectures.

The methodology employed in the research article is grounded in established practices of graphology, machine learning, and image processing. By utilising decision trees, SVM, and KNN algorithms for classification, the study aligns with common approaches in machine learning research. The feature extraction process, which includes baseline, top margin, line spacing, word spacing, letter size, slant, and pen pressure, is conducted using the OpenCV library—a widely used tool for image processing. Figure 2. 1 below shows how the framework and process done by (Samsuryadi et al., 2023)

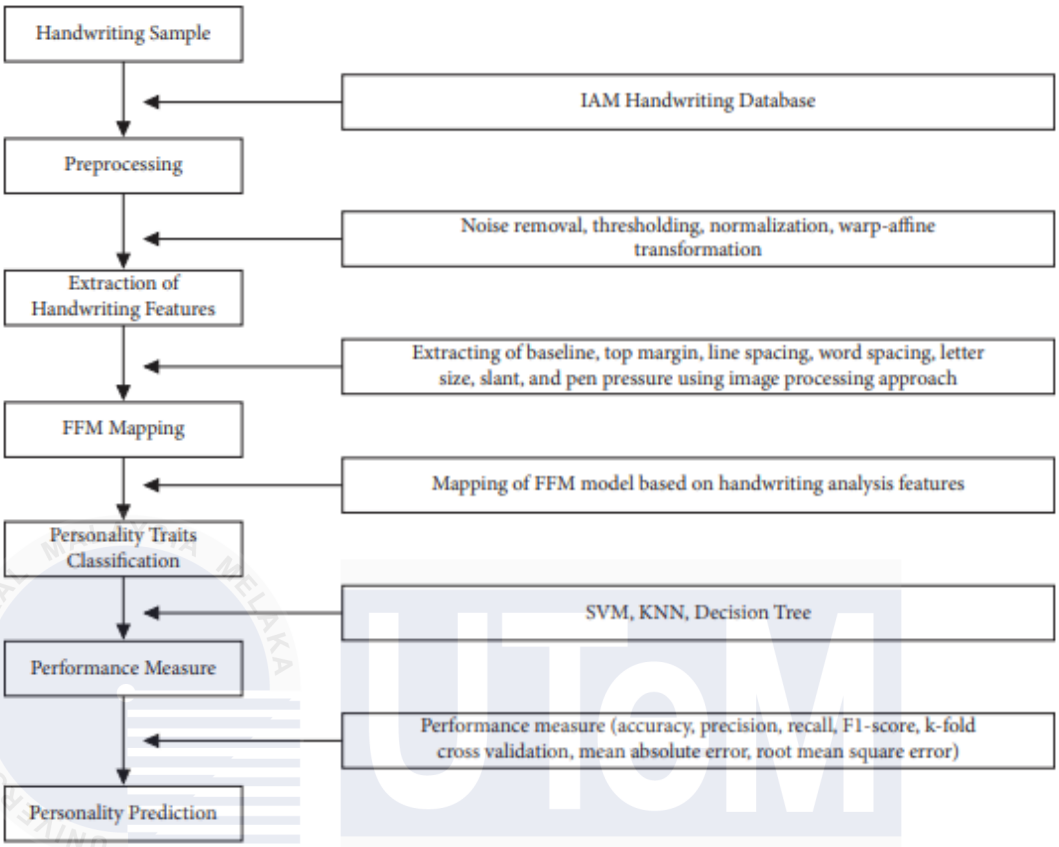


Figure 2. 1 Proposed framework from (Samsuryadi et al. 2023)

The research article presents the results of experiments conducted using the proposed framework, showcasing accuracy rates exceeding 99% in predicting personality traits based on handwriting features. This high level of accuracy underscores the effectiveness of the framework in classifying personality traits according to the Big Five model (OCEAN). By mapping handwriting features to psychological traits, the study contributes to the advancement of automated graphology and offers valuable insights into the intricate relationship between handwriting characteristics and personality traits. The relationship between the Big Five Model personality and handwriting features are as shown in Table 2.1 until Table 2.8 respectively.

Table 2. 1 Correlation between OCEAN and Graphology Features

Big Five Personality	Graphology Features
Neuroticism	Descending baseline and moderately inclined slant angle
Openness to experience	Small line spacing, normal word spacing, and moderately inclined slant angle
Extroversion	Ascending baseline, big letter size, heavy pen pressure, and extremely inclined slant angle
Agreeableness	Wide top margin, light pen pressure, and moderately reclined slant angle
Conscientiousness	Straight baseline, small letter size, heavy pen pressure, and extremely reclined slant angle

Table 2. 2 Baseline features and their descriptions

Baseline	Description
Ascending	Optimism, escape the demands of routine
Straight	Mind disciplines his/her emotions
Descending	Pessimism, fatigue, and depression

Table 2. 3 Line spacing features and their descriptions

Line Spacing	Description
Wide	Isolated and extravagant
Normal	Flexibility and harmony
Narrow	Confused mind, lively, forceful, lack of clarity, and poor concentration

Table 2. 4 Letter size features and their descriptions

Letter Size	Description
Big	Acts with boldness, enthusiasm, optimism, boastfulness, and restlessness
Normal	Practical and realistic
Small	Not very communicative except with close friends

Table 2. 5 Word Spacing features and their descriptions

Word Spacing	Description
Wide	Maintain his distance from social contact, privacy, and isolated
Normal	Flexibility, objectively, social maturity, intelligence, and inner organization
Narrow	Crowd others for attention, craving constant contact, closeness, and selfish

Table 2. 6 Top Margin features and their descriptions

Top Margin	Description
Wide	Modesty and formality
Narrow	Informality, the directness of the approach, lack of respect, and indifference

Table 2. 7 Pen Pressure and their descriptions

Pen Pressure	Description
Heavy	Strong-willed, firm, can get easily excited, stubborn, and inclined to depression
Normal	Healthy vitality and willpower
Light	Sensitive and impressionable

Table 2. 8 Slant angle features and their descriptions

Slant angle	Description
Straight (0°)	Head-over-heart emotional attitude, cautious, and consider responses
Little inclined (5° or 15°)	Normally sensitive and emotionally healthy but modest with responses
Moderately inclined (30°)	Express their emotional self impulsively and feelings will influence decisions
Extremely inclined (45°)	Volcano of emotional reactions: extremely ardent, passionate, jealous, easily offended, and very demonstrative

	with affections
Moderately reclined (−5° or −15°)	Polish, repressed fears, and resist accepting progress or change
Extremely reclined (−30° or −45°)	Independent, hard to fathom, and difficult to get along with
Irregular (unstable)	Unsettled and inconsistent

There are several equations to measure the performance of the analysis. The equation for each performance measures are listed as below:

$$(TP + TN/TP + TN + FP + FN)$$

This equation represents of how to measure the performance of the accuracy. With the input patterns are TP = True Positive, TN = True Negative, FP = False Positive.

Next, the precision is measured by the equation below to get the precise result to continue a performance measure.

$$(TP/TP + FP)$$

To calculate the recall, it also has its own calculation and equation. The equation as stated as below:

$$(TP/TP + FN)$$

Last but not least, to measure the F1 Score, the result of precision and recall must be obtained first before calculating it. Therefore, the equation for F1 Score is as stated below:

$$(Precision * Recall/Precision + Recall)$$

In terms of hardware and software, the project utilises the IAM handwriting database for training and testing, image processing tools like the OpenCV library for feature extraction, and machine learning algorithms such as decision trees, SVM, and KNN for classification. These tools and technologies play a crucial role in processing handwriting images, extracting relevant features, and applying machine learning techniques to accurately predict personality traits based on graphological analysis (Marti et al., 2002).

2.2.3 Technique

Different machine learning and computer vision approaches have been used in the field of AI-based handwriting analysis to extract personality features from handwriting photographs. K-nearest neighbours (KNN) (Tan, 2006), Support Vector Machines (SVM) (Malathi et al., 2019), Decision Trees (Topaloglu, 2017), Random Forests (Likforman-Sulem et al., 2015), Artificial Neural Networks (ANN) (Gavrilescu, 2015), and Convolutional Neural Networks (CNN) (Fatimah et al., 2019) are some of the most often used techniques. These methods are selected because of their effectiveness in classification tasks and their capacity to handle high-dimensional data. With these advancements in technology, several automated approaches leveraging machine learning and computer vision have emerged. This section explores various techniques and justifies the chosen methods for this project.

2.2.3.1 K-Nearest Neighbours (KNN)

KNN is a straightforward and effective classification algorithm used in handwriting analysis. It operates by identifying the k-nearest data points in the feature space and assigning the most common class among them to the new data point. This method is particularly effective when there is a well-defined distance metric, and it can be used incrementally to improve the model's accuracy over time (Joshi et al., 2015). However, the main drawback of KNN is its computational cost during the prediction phase, especially with large datasets, which can slow down the analysis process.

The K-Nearest Neighbours (KNN) algorithm is utilised as a classification tool to predict personality traits based on handwriting features extracted from the IAM handwriting database. In this task, the KNN algorithm assigns a personality trait

label to a new handwriting sample by analysing the traits of the K nearest neighbours in the feature space. This method leverages the proximity of similar handwriting samples to infer personality characteristics.

Handwriting features are meticulously extracted from the handwriting images within the IAM database through advanced image processing techniques. These extracted features serve as the input for the KNN algorithm, which uses them to predict personality traits. The feature extraction process is critical, as the quality and relevance of these features directly impact the accuracy of the personality trait predictions (Samsuryadi et al., 2023).

The performance of the KNN algorithm, along with other machine learning techniques such as Support Vector Machines (SVM) and decision trees, is evaluated using a range of metrics. These metrics include accuracy, precision, recall, and F1 score, which collectively help assess the effectiveness of the KNN algorithm in predicting personality traits. This comprehensive evaluation ensures that the model's predictions are both reliable and valid.

The IAM handwriting database is divided into training and testing sets using a split ratio of 20:80. This division allows the KNN algorithm to learn patterns and relationships from the training data and subsequently evaluate its performance on the unseen test data. Such a split ratio ensures that the model is well-trained while also providing a robust assessment of its generalisation capabilities.

The performance of the KNN algorithm is measured in terms of its ability to accurately classify personality traits, including OCEAN. The results from this performance measurement are thoroughly analysed to determine the effectiveness of KNN in predicting these specific traits. The analysis provides insights into the algorithm's strengths and limitations in the context of handwriting-based personality prediction.

2.2.3.2 Support Vector Machines (SVM)

SVM is another powerful technique used for handwriting analysis due to its robustness in high-dimensional spaces. SVM works by finding the hyperplane that best separates the classes in the feature space (Lauer et al., 2006). It is particularly useful for binary classification problems and has been successfully applied to identify personality traits from handwriting samples (Pervouchine and Leedham, 2006). Despite its advantages, SVM can be less effective when dealing with multiclass problems and may require extensive parameter tuning to achieve optimal results. The hyperplane can separate optimally by finding output with the equation below:

$$f\ (x)\ =\ \text{sign}\ (x^T w\ +\ b)$$

With the input pattern is x and where the bias b and the vector of weights w are trained by maximising the margin.

The result of the separating rule as below is based on the support vectors (SVs) and their corresponding Lagrange multipliers αi. These SVs are the training patterns that lie on the margin boundaries. One key advantage of this algorithm is its sparsity, as it only uses a small subset of the training examples to compute the classifier's output.

$$f(x) = sign\left(\sum_{support\ vectors} yi\ \alpha i(x_i^T x) + b\right)$$

The SVM algorithm is highlighted as a pivotal component of the classification framework designed for predicting personality traits through handwriting analysis. SVM, a well-established supervised learning algorithm renowned for its efficacy in classification tasks, is strategically leveraged to enhance the accuracy and precision of personality trait prediction based on handwriting features. By harnessing the inherent capabilities of SVM in delineating complex decision boundaries and

maximising classification accuracy, the research underscores the significance of SVM in facilitating robust and reliable personality trait predictions within the context of automated graphology. Through the development of a classification framework centred around SVM, the study aims to capitalize on the algorithm's strengths in handling intricate classification tasks, ultimately contributing to the advancement of automated personality assessment methodologies grounded in handwriting analysis.

2.2.3.3 Decision Trees and Random Forests

Decision Trees classify handwriting samples by learning decision rules inferred from the data features. They are easy to interpret and can handle both numerical and categorical data. However, they tend to overfit the training data, which can limit their generalizability. To mitigate this issue, Random Forests, an ensemble method of multiple decision trees, can be used. Random Forests improve classification accuracy and reduce overfitting by averaging the results of numerous decision trees trained on different parts of the dataset (Joshi et al., 2015). The downside is that they can become complex and less interpretable compared to single decision trees.

2.2.3.4 Convolutional Neural Networks (CNN)

CNNs are a class of deep learning algorithms designed for processing grid-like data such as images. They automatically learn hierarchical feature representations, making them highly effective for image recognition tasks, including handwriting analysis. CNNs can handle variations in handwriting style, size, and orientation. However, they require large datasets and significant computational resources for training. The ability of CNNs to extract and learn features from raw image data makes them particularly suitable for complex handwriting analysis tasks where traditional feature extraction methods may fall short (Kumar et al., 2022). CNN will made the preprocessing which the images were normalised and enhanced, with text segmented into lines and words. In addition, the CNNs were used to automatically

extract features from the handwriting samples. These features included slant, baseline, pen pressure, and letter design. Figure 2.3 shows an example of the architecture of CNN.

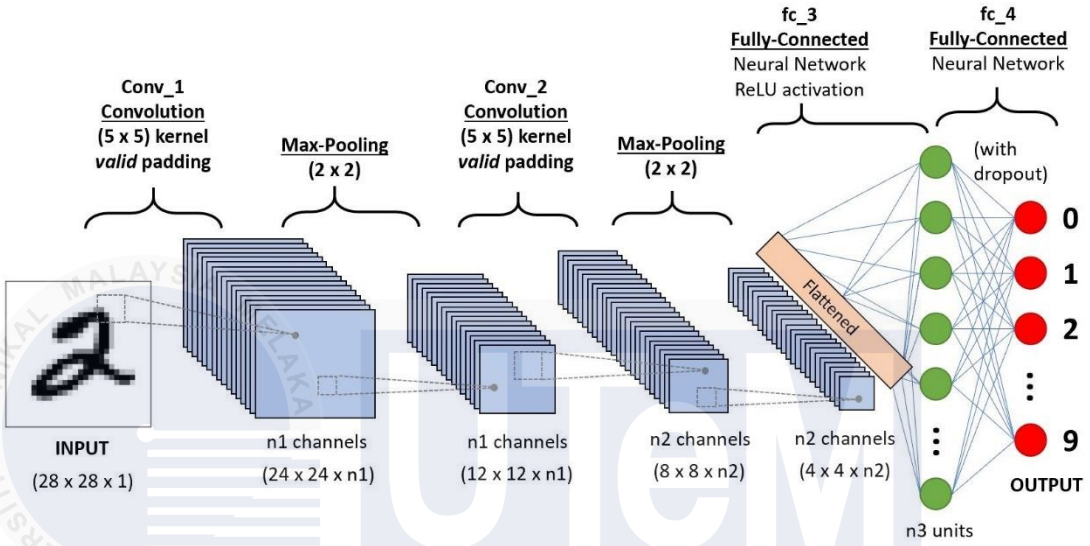


Figure 2. 2 Architecture of CNN

In the research article by Samsuryadi et al., the Convolutional Neural Network (CNN) algorithm emerges as a pivotal tool for image analysis and pattern recognition, particularly in the context of handwriting analysis for personality trait classification. The study introduces the PersonaNet algorithm, which is built upon the CNN model, as a sophisticated approach to classifying personality traits based on handwriting features extracted from the dataset. By harnessing the deep learning capabilities of CNN, PersonaNet demonstrates its prowess in effectively analysing handwriting patterns and extracting meaningful features essential for personality trait prediction. The utilization of CNN within the PersonaNet algorithm underscores its ability to discern intricate patterns within handwriting samples, enabling accurate and reliable classification of personality traits according to the OCEAN.

2.2.3.5 Artificial Neural Network (ANN)

ANNs are inspired by the human brain and consist of interconnected neurons that process information. They have been used in handwriting analysis to learn complex patterns in data. ANNs can capture non-linear relationships and interactions between features. However, they require large amounts of data for training and can be prone to overfitting. Additionally, their "black-box" nature makes them less interpretable than other methods. Despite these challenges, ANNs have shown significant promise in recognising complex handwriting features and improving classification accuracy (Richa et al., 2023). Figure 2.3 shows the ANN basic architecture and how it works.

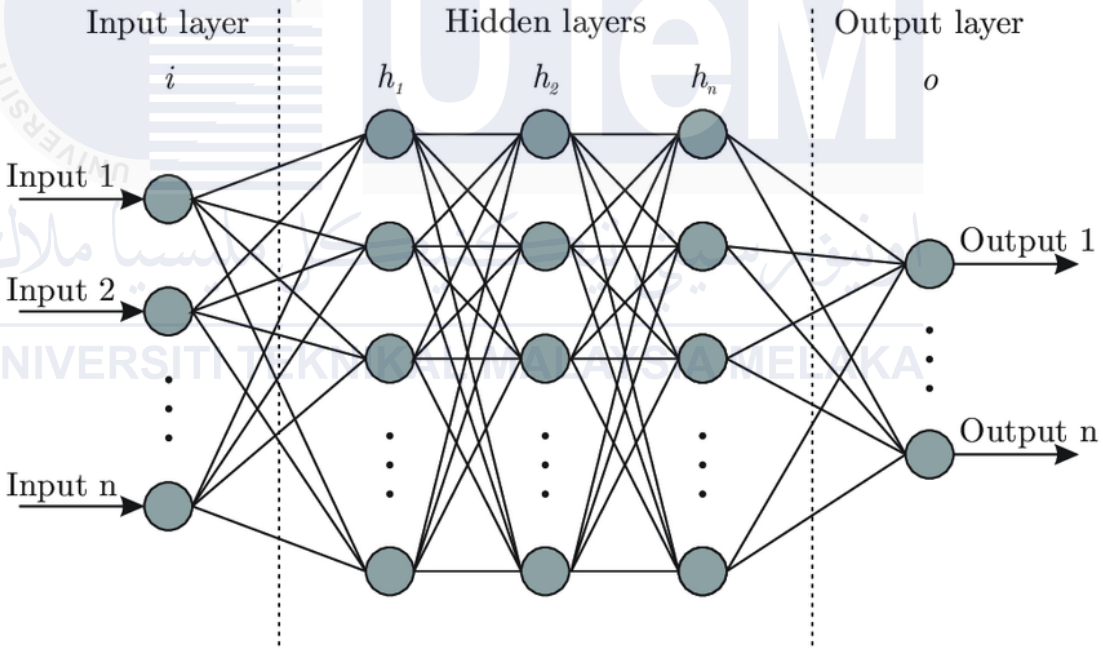


Figure 2. 3 ANN basic architecture

The research discusses the integration of artificial neural networks (ANN) with psychological measurements such as the Myers-Briggs Type Indicator (MBTI) to analyze handwriting features for personality assessment. By utilizing ANN's parallel processing and adaptive learning, the study aims to decode the relationship between

handwriting patterns and personality traits. This fusion of machine learning and psychological frameworks seeks to enhance the accuracy of personality trait prediction based on intricate handwriting analysis.

2.2.3.6 Template Matching

Template matching involves comparing segments of the handwriting image with pre-defined templates to identify features. This method is straightforward and works well for recognizing standard shapes. However, it can be inflexible to variations in individual handwriting styles and can be computationally intensive. Template matching is best suited for applications where handwriting styles are relatively uniform and predictable, which is often not the case in real-world scenarios (Sharma et al., 2023).

In the context of handwriting analysis, for example, template matching is employed to analyse the height of the t-bar on the stem of the letter 't' and the word-slant. The technique involves predefining several templates of the letter 't' with variations in the height of the t-bar (very low, mid-level, very high, and out of the stem). These templates are then matched with the characters in the handwriting sample using the Hamming distance method. The Hamming distance measures the minimum number of substitutions required to change one template into another, ensuring precise matching of the handwritten character with the predefined templates (Joshi et al., 2015). Figure 2.4 shows the the example of template matching for a letter “t”.

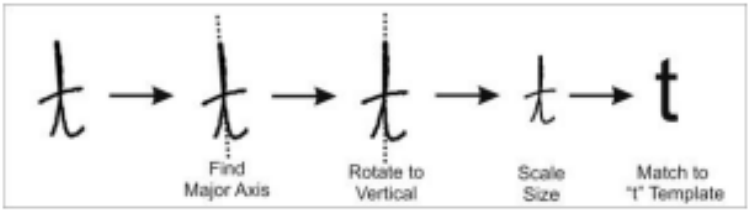


Figure 2. 4 Template Matching for letter ‘t’ by (Joshi et al., 2015)

This method is advantageous for its simplicity and effectiveness in environments with high contrast, such as black handwriting on white paper. However, the accuracy of template matching can be influenced by the quality of the template images and the resolution of the scanned handwriting samples. Despite these challenges, template matching remains a robust tool for identifying specific handwriting features that are crucial for personality analysis.

2.3 Project Methodology

This part of the project methodology acts as a guide or standard to ensure that the project stays on course. The selected methodology is the Agile Method. This life cycle model defines the project management methodology that focuses on ongoing cooperation and progress and divides the work into phases of the cycle and the order in which they are completed. Each stage produces deliverables that are needed for the next stage of the life cycle, as illustrated in the figure 2.5 below.

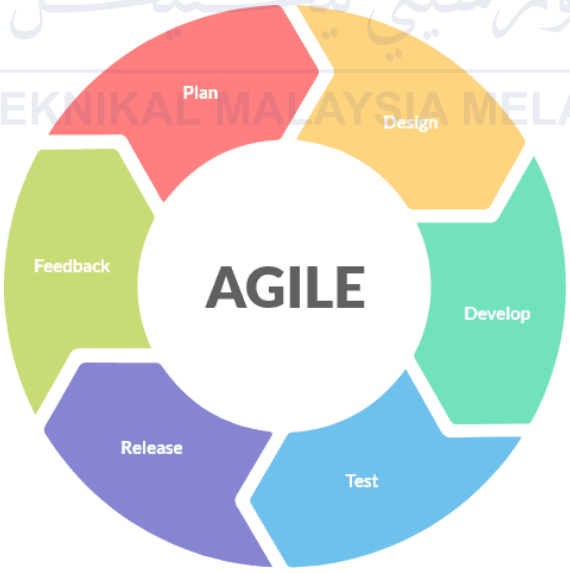


Figure 2. 5 Agile Methodology Phases

A sequential life cycle model known as the agile methodology in as illustrated in Figure 2.5, defines its application in the development of the AI-Based Handwriting Analysis system. This model comprises distinct phases, including Plan, Design, Develop, Test, Release and Feedback. Additionally, each phase must be executed in sequence without any overlap, ensuring that the subsequent phase only commences once the previous one is completed.

2.3.1 Plan

During the planning phase, the focus is on gathering information about the project requirements to ensure a clear understanding of the objectives. Additionally, a detailed project plan is developed, outlining the scope, timeline, resources, and milestones, to ensure awareness of the project's trajectory. Meetings with stakeholders, including the domain expert from Medipro Venture Sdn. Bhd., are conducted to capture specific needs and expectations for the handwriting analysis system. Functional and non-functional requirements of the web application are defined, creating a comprehensive blueprint for the project.

2.3.2 Design

In the design phase, the architecture and components of the system are meticulously planned. High-level architecture diagrams are created to map out the system components and their interactions. The design of the user interface (UI) and user experience (UX) is prioritised to ensure the web application is intuitive and user-friendly. Data flow and the database schema are defined to manage handwriting images and analysis results efficiently. Additionally, appropriate AI techniques are selected, including machine learning models for pattern recognition and computer vision algorithms for image processing, to ensure the system's technical robustness. Design the calculation of each handwriting feature that wants to implement into the system for the computer vision categorize each feature. The features are baseline angle, top margin, letter size, line spacing, word spacing, pen pressure and slanting

angle. The calculations for each handwriting features are designed as Table 2.9 until 2.15 below:

Table 2. 9 Baseline Angle Determination

Baseline Angle	Description
≥ 0.2	DESCENDING
≤ -0.3	ASCENDING
-0.3 < baseline angle < 0.2	STRAIGHT

Table 2. 10 Top Margin Determination

Top Margin	Description
≥ 1.7 cm	MEDIUM OR BIGGER
< 1.7 cm	NARROW

Table 2. 11 Letter Size Determination

Letter Size	Description
≥ 18 pt	BIG
< 13 pt	SMALL
13 pt comput> letter size < 18 pt	MEDIUM

Table 2. 12 Line Spacing Determination

Line Spacing	Description
≥ 3.5	BIG
< 2	SMALL
2 < line spacing < 3.5	MEDIUM

Table 2. 13 Word Spacing Determination

Word Spacing	Description
>2	BIG
< 1.2	SMALL
2 > word spacing > 1.2	MEDIUM

Table 2. 14 Pen Pressure Determination

Pen Pressure	Description
> 180	HEAVY
< 151	LIGHT
151 > pen pressure < 180	MEDIUM

Table 2. 15 Slant Angle Determination

Slant Angle	Description
= -45 or -30	EXTREMELY RECLINED
= -15 or -5	A LITTLE OR MODERATELY RECLINED
= 5 or 15	A LITTLE INCLINED
= 30	MODERATELY INCLINED
= 45	EXTREMELY INCLINED
= 0	STRAIGHT
= 180	IRREGULAR

2.3.3 Develop

Throughout the development phase, the works are actively ongoing to construct the AI-based handwriting analysis system in a series of iterative steps. By employing agile sprints, this phase concentrate on incorporating particular features and components within defined time frames. This phase is where the writing and integration of code for data preprocessing, feature extraction, and training of the model. The model will be integrated into the web app to make the webpage responsive and function well. The framework used to develop the web page with computer vision techniques are the Flask and Visual Studio Code. Continuous progress is ensured through regular code reviews and daily stand-up meetings with the SV, enabling quick resolution of any issues. This phase places emphasis on collaboration, flexibility, and incremental development to effectively address any changing requirements.

2.3.4 Test

In the Testing phase, the system is put through a thorough review process to make sure it works as intended and is error-free. Next, the integration testing is done to make sure various system components function together smoothly after unit testing is done on individual components to confirm their functioning. Initial User acceptance testing (UAT) is carried out to confirm that the system meets the specified requirements and expectations, ensuring a high level of satisfaction. The evaluation phase includes checking the developed system to make sure it meets the specific requirements and performs as expected. Different testing techniques, such as unit tests, integration tests, and system tests, are used to confirm the accuracy of each part of the AI model. Ongoing testing throughout the sprints aids in promptly identifying and rectifying any bugs, ensuring a top-notch product.

2.3.5 Release

During the release phase, the AI-powered handwriting analysis system is prepared for deployment in a live environment. This entails bundling the software, conducting comprehensive integration tests, and creating deployment guidelines. A detailed release plan is put into action to introduce the system to end-users, with the goal of minimizing any interruptions and maximizing ease of use. Additionally, this phase involves training both users and stakeholders, myself, handwriting expertise and also Dr. Elle on how to utilise the system effectively, as well as offering initial support to tackle any issues that may arise after deployment.

2.3.6 Feedback

The feedback phase is critical for the continuous improvement of the system. After release, feedback is collected from users, stakeholders, and performance monitoring tools which are mainly obtained from the domain expert herself. This feedback helps identify areas for enhancement and any new requirements or issues that were not previously anticipated. With this feedback, I may know what elements should prioritise future iterations and updates, ensuring the system evolves to better meet user needs and maintain high performance and accuracy. Regular updates and enhancements are provided based on user feedback and changing requirements, ensuring the system remains relevant and efficient. Ongoing support is offered to users, including the domain experts, to assist with any questions or challenges encountered while using the system, ensuring long-term success and user satisfaction before being released to the industry market.

2.4 Project Requirements

This section will include a list of the software and hardware that this project used to accomplish its goals and serve its purposes.

2.4.1 Software Requirements

i. **Visual Studio Code**. A source-code editor to create a website and deploy the model into a local server.
ii. **Flask.** A lightweight and flexible Python web framework used for building web applications quickly and efficiently.
iii. **OpenCV.** An open-source computer vision library that provides a wide range of tools and functions for image and video processing in Python.
iv. **Microsoft Office.** For report writing purposes, and to store data and backup the report. For instance, Microsoft Word.
v. **Canva.** A graphic design tool that allows users to create professional-looking designs. In this case, it is used for creating the project slide presentation.

2.4.2 Hardware Requirements

i. Laptop

   a. Processor: 11th Gen Intel(R) Core(TM) i5-1155G7 @ 2.50GHz 2.50 GHz
   b. Installed RAM: 8.00 GB (7.75 GB usable)
   c. System type: 64-bit operating system, x64-based processor
   d. Windows type: Windows 11

2.5 Project Schedule and Milestones

In this part, there is a breakdown of the project Gantt Chart in Table 2.16, and Table 2.17 outlines the milestones for the project schedule, including the proposal, development, and report phases.

Table 2. 16 Gantt Chart

Task	Week														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PSM I															
Proposal PSM								MI							
Proposal Correction								DS							
Chapter 1								EM							
Chapter 2															
Chapter 3															
Chapter 4								BR							
PSM report															
Project Demo								EA							
Presentation PSM I								K							

Table 2. 17 Project Milestone

Week	Activity	Description
1	Project discussion with the supervisor	Objective and scope
	Proposal assessment	Assess by supervisor
2	Proposal submission	Repair any flaws and make corrections before submitting
3	Chapter 1	Start Chapter 1 and project development
4	Chapter 1	Chapter 1 completion and start Chapter 2
	Chapter 2	Literature review, facts finding & methodology
5	Chapter 2	Keep finding research
	Chapter 2	Research in methodology and Chapter 2 completion
6	Chapter 3	Start Chapter 3 for the analysis
7	Chapter 3	Problem, requirement analysis here
	Chapter 4	Begin Chapter 4
8	**MIDSEM BREAK**	
9	Chapter 4	Design the architecture
10	Chapter 4	Chapter 4 Completion
11	Project Demo to SV	Demo the basic analysis
12	Project Demo to SV	Improve the project, coding, analysis, features.
	PSM I report	Begin the PSM I report

13	Project Demo to SV	Present the current project, ask for improvements and suggestions
14	PSM I report	Completion of PSM I report and development
	Project Demo	
15	Presentation of PSM I and Submission of PSM I report	Presentation to SV and evaluator of the PSM I

2.6 Conclusion

In any research project, conducting a thorough literature review and a meticulous methodology are crucial components. The literature review serves as a means to collect valuable insights from previous research endeavours related to the topic at hand. This involves sourcing information from articles, journals, and books to build a comprehensive understanding of the subject matter. Equally important is the careful and systematic approach to analysis in the methodology. Subsequently, the following chapter will focus into the project's analysis, encompassing problem analysis and requirement analysis.

CHAPTER 3: ANALYSIS

3.1 Introduction

The analysis phase is vital whenever a research or project begins as it determines the criteria to accomplish the task. Hence, the whole part of the analysis phase is required to make the project progress smoothly. Problem analysis and requirement analysis are the elements in the analysis phase that have to be done. Generally, computer vision has made many breakthroughs by achieving top scores on many tasks and related competitions. In this project, computer vision and Machine Learning model were utilised. The libraries used to train the models in this project to analyse handwriting are Scikit-learn. Each model has a different architecture. It means that these models have their own each calculation of handwriting features. To determine which model is the best for classifying handwriting features, each image's accuracy will be measured, log-loss, and AUC-ROC and will be processed in the backend system. The high precision, low log-loss, and high value of AUC-ROC indicate the best model. The datasets of the image are gained from dataset provided by the domain expert from Medipro Ventures Sdn. Bhd. that was assisted by Dr. Elle.

3.2 Problem Analysis

Medipro Ventures is looking to revolutionize their handwriting analysis services by creating an AI-powered system that will support the domain expert, their renowned graphologist. Their current manual analysis process is slow, based on individual judgment, and difficult to expand. Currently she’s using Microsoft Excel manually and refers to the research books. This consumes a lot of time to analyse. The proposed system aims to automate the extraction of handwriting characteristics as Table 3.1 until 3.7 below:

Table 3. 1 Baseline Types

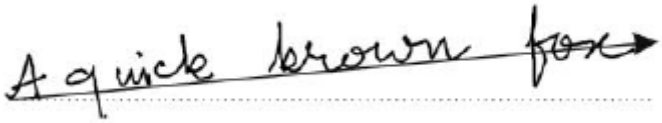
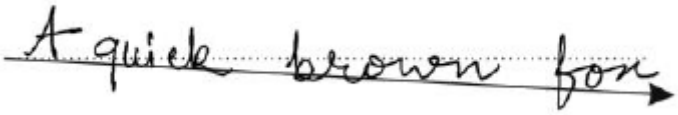
Baseline	Example
Ascending	
Descending	
Straight	

Table 3.1 shows the Baseline Types and its example for each features.

Table 3. 2 Top Margin Types

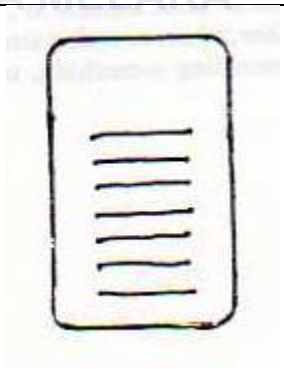
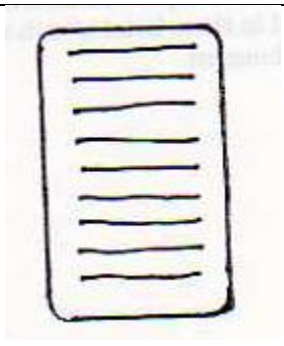
Top Margin	Example
Medium or Bigger	
Narrow	

Table 3.2 shows the Top Margin Types and its example for each features.

Table 3. 3 Letter Size Types

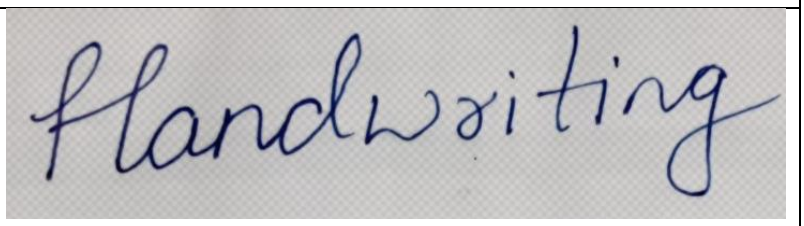
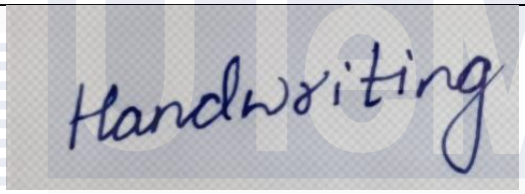
Letter Size	Example
Big	
Small	
Medium	

Table 3.3 shows the Letter Size Types and its example for each features.

Table 3. 4 Line Spacing Types

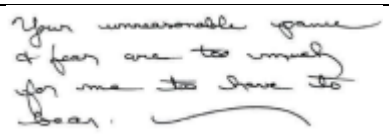
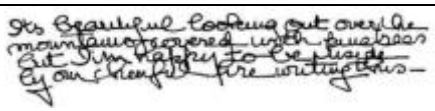
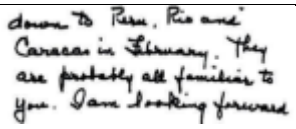
Line Spacing	Example
Big	
Small	
Medium	

Table 3.4 shows the Line Spacing Types and its example for each features.

Table 3. 5 Word Spacing Types

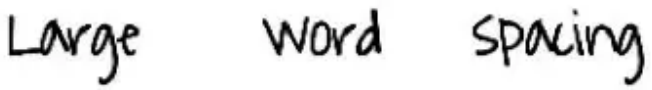
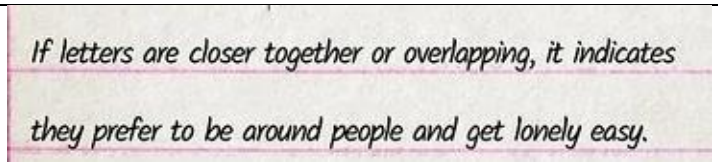
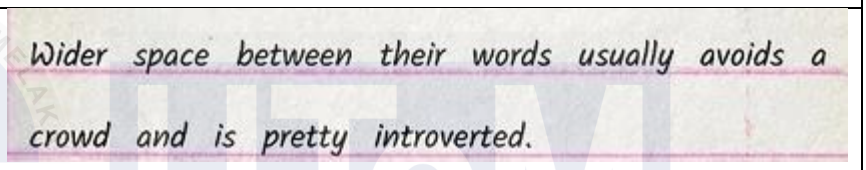
Word Spacing	Example
Big	
Small	
Medium	

Table 3.5 shows the Word Spacing Types and its example for each features.

Table 3. 6 Pen Pressure Types

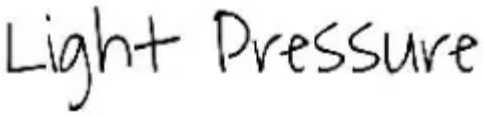
Pen Pressure	Example
Heavy	
Light	
Medium	

Table 3.6 shows the Pen Pressure Types and its example for each features.

Table 3. 7 Slant Angle Types

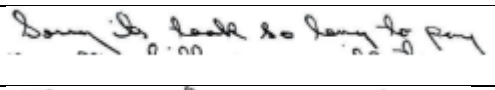
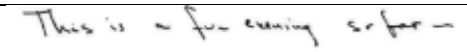
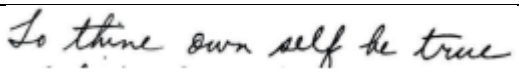
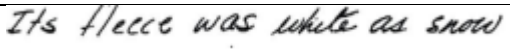
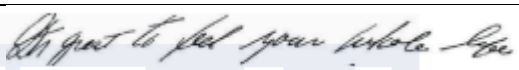
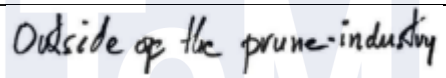
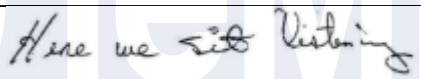
Slant Angle	Example
Extremely reclined (-30° or -45°)	
A little or moderately reclined (-15° or -5°)	
A little inclined (5° or 15°)	
Moderately inclined (30°)	
Extremely inclined (45°)	
Straight (0°)	
Irregular	

Table 3.7 shows the Slant Angle Types and its example for each features.

These features will be correlated with personality traits using machine learning. This approach will not only improve efficiency, accuracy, and consistency but also enable the handling of large volumes of samples and the generation of comprehensive reports. The system will seamlessly integrate with existing workflows, ensuring high data quality, user acceptance, and security, while also addressing potential risks related to model accuracy and technical issues.

There are 8 classifiers to train the models. The classifiers included are for the 8 personality traits respectively which are explained in the Table 3.8 below:

Table 3. 8 Personality traits with descriptions

Personality Traits	Descriptions
Emotional Stability	Emotional stability refers to a person's ability to

	remain calm, resilient, and consistent in mood and behavior, even under stress or pressure. Individuals with high emotional stability typically handle challenges and negative emotions with composure and adaptability, whereas those with lower emotional stability may experience more frequent mood swings, anxiety, or impulsiveness.
Mental Energy or Willpower	Mental energy or willpower is the capacity to focus, resist distractions, and persist in tasks despite challenges. It encompasses the mental stamina required to maintain attention, control impulses, and achieve goals. High mental energy enables sustained effort and resilience, while low mental energy can lead to fatigue, procrastination, and difficulty in overcoming obstacles.
Personal Harmony and Flexibility	Personal harmony is the state of inner balance and peace, where one's thoughts, emotions, and actions are in alignment, fostering a sense of well-being and contentment. Flexibility is the ability to adapt thoughts, behaviors, and emotions to changing circumstances, demonstrating resilience and openness to new experiences and challenges.
Modesty	Modesty is the quality of having a humble and unassuming view of one's own abilities, achievements, or importance. It involves recognizing one's strengths and successes without seeking excessive attention or praise, and valuing others' contributions and perspectives. Modesty promotes a balanced self-view and fosters respectful and harmonious relationships with others.
Lack of Discipline	Lack of discipline is the inability to consistently control one's actions, impulses, and desires to achieve long-term goals. It manifests as procrastination,

	inconsistency, and difficulty in following through with commitments or maintaining focus on tasks. This can lead to unmet goals, reduced productivity, and a general sense of disorganization.
Poor Concentration	Poor concentration is the difficulty in maintaining attention and focus on a task or activity for a sustained period. It often leads to frequent distractions, incomplete tasks, and a reduced ability to absorb and retain information. Causes can include stress, fatigue, and environmental factors, impacting productivity and learning.
Non-Communicativeness	Non-communicativeness is the tendency to refrain from sharing thoughts, feelings, or information with others. It manifests as limited verbal interaction, reluctance to engage in conversations, and a preference for silence or minimal responses. This trait can hinder effective communication and social connection, making it difficult to express needs, build relationships, or collaborate effectively.
Social Isolation	Social isolation refers to the state of being separated from social interactions or relationships with others. It involves limited participation in social activities, minimal contact with friends or family, and a sense of disconnection from the broader community. Social isolation can result from various factors such as geographic distance, physical health issues, mental health conditions, or personal preferences. It can lead to feelings of loneliness, depression, and reduced overall well-being if not addressed.

However, a system to determine the type of personality traits without spending much time analysing handwriting manually, currently has made a breakthrough in computer vision and machine learning specifically. Additionally, the calculations of

certain handwriting features differ from each other. The process of training to classify handwriting features, their accuracy, log-loss and AUC-ROC value are the considered factors.

3.3 Requirement Analysis

This section will outline the necessary requirements for completing the project, including objectives and scope. The requirements to be addressed include Data, Functional, Non-functional, and Others Requirement.

3.3.1 Data Requirements

In this analysis, the whole handwriting image dataset is acquired from the existing project collaboration with a graphology company named Medipro Ventures. The dataset was collected by giving out a blank paper and a ball pen to participants or volunteers. The participants are required to write anything they can think of such as feelings, hobbies, etc as long as it is long enough and readable. The participants also can write freely on the paper. Next, the handwritten documents were collected and converted into images as the dataset. For the time being, the dataset has around 1600 images, of which 85% are for training and another 15% are for validation or testing.

3.3.2 Functional Requirement

A functional requirement outlines the necessary components and functions within a system. These requirements encompass calculations, technical specifications, data manipulation, and other necessary functionalities crucial for achieving the project's objectives. Most of this requirements stored in “categorize” directory. The dataset to be used is already specified in the Data Requirements and is stored in the "img" folder.

Firstly, the images from the "img" directories were taken to use them to train the models and fit the classifiers in the "train_predict" phase. Following this, we evaluate and validate the models using the images from the "sample test png" folder. Their performance is then assessed based on their accuracy, log-loss, and AUC-ROC value.

3.3.3 Non-functional Requirement

A non-functional requirement is crucial to determine the specific criteria used to evaluate the model. By using these criteria, the score for each model's performance need to be recorded. This is important to evaluate each classifier model that is the best for handwriting analysis model deployment before integrating into the web application. The standards of non-functional requirements are as follows:

1. Accuracy: The average accuracy recorded while testing the model.
2. Training Time: Time taken for these models to be trained.
3. Loss: The losses when training the model were differences of log-loss value ±0.01.
4. Trained Model Size: Size of the model file after training in MB in pickle.

3.3.4 Others Requirement

In this section, the detailed analysis of software and hardware requirement listed and discussed.

3.3.4.1 Software Requirements

i. Visual Studio Code

Visual Studio Code is a versatile source code editor that supports a wide range of programming languages such as JavaScript, Python, JSON, HTML, and CSS. It can be used in conjunction with Flask, a Python framework for web applications, which offers essential features for URL routing and page rendering. This editor is commonly utilised for web design and deploying models onto websites.

ii. Microsoft Word

Microsoft Word is a graphical word processing software that allows users to create documentation and save files in Word format. Developed by Microsoft and officially launched in 1981, it offers various tools such as a spelling and grammar checker, and the ability to insert pictures as well as create tables. Microsoft Word is widely used for creating proposals, reports, and other project documentation.

iii. Flask

Flask is a lightweight Python web framework that allows users to quickly and easily create web applications. It is a popular choice for web development due to its simplicity and flexibility. Flask is open-source and has a large and active community of users. It can be used to create everything from small, static sites to complex, data-driven web applications. Flask is known for its micro testing capabilities and its ability to handle asynchronous programming**.**

3.3.4.2 Hardware Requirements

In this section, requirements for the hardware as shown in Table 3.9 below.

Table 3. 9 Hardware Requirements

Processor	11th Gen Intel(R) Core(TM) i5-1155G7 @ 2.50GHz
Installed Memory (RAM)	8 GB
System Type	64-bit Operating System, X64-based processor
Operating System	Windows
Edition	Windows 11
Graphic Processing Unit	Intel(R) Iris(R) Xe Graphics
Memory Capacity	4 GB

3.4 Conclusion

In this chapter, the problem was analysed, the requirements needed to complete the project were identified, and an overview understanding the objectives of the project should accomplish. A further analysis was conducted to streamline the project's processes. The next chapter will focus on the design of the proposed technique.

CHAPTER 4: DESIGN

4.1 Introduction

In order to ensure the system runs smoothly and meets its objectives, the design phase is crucial. This part of the project will focus on outlining the design process for the complete image classification system, encompassing its functions and components. It will offer comprehensive insights into the intended operations of the system. Additionally, Visual Studio Code IDE along with Python, HTML, CSS, and other frameworks will be leveraged to craft the system interfaces.

4.2 High-Level Design

The diagram in Figure 4.1 provides a high-level overview of the system design. It illustrates how the trained model is incorporated into a web application. The Flask web framework is utilised to create additional interfaces for launching web applications. Furthermore, the algorithm is modified and embedded into the code to ensure seamless integration with the web application.

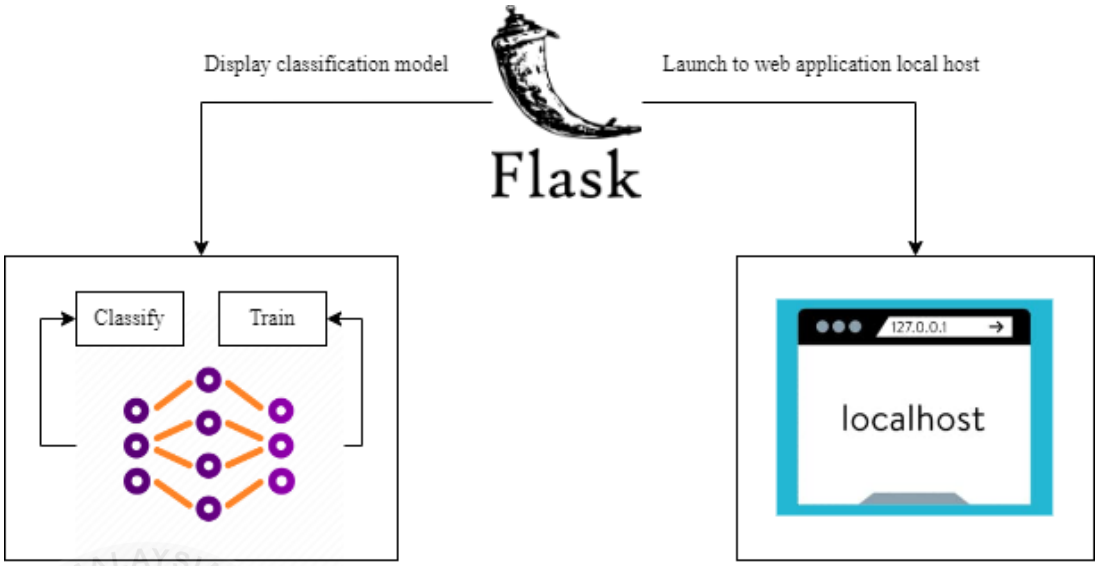


Figure 4. 1 High Level Design

4.2.1 System Architecture

Meanwhile, for Figure 4.2 below, it shows an overview of the system architecture. The architecture consists of the interaction between the user and the AI-Based Handwriting Analysis system. The web server will respond to the user's request and display it to the user. This system was developed using Python and utilised the AI techniques which are image classification, computer vision and machine learning.

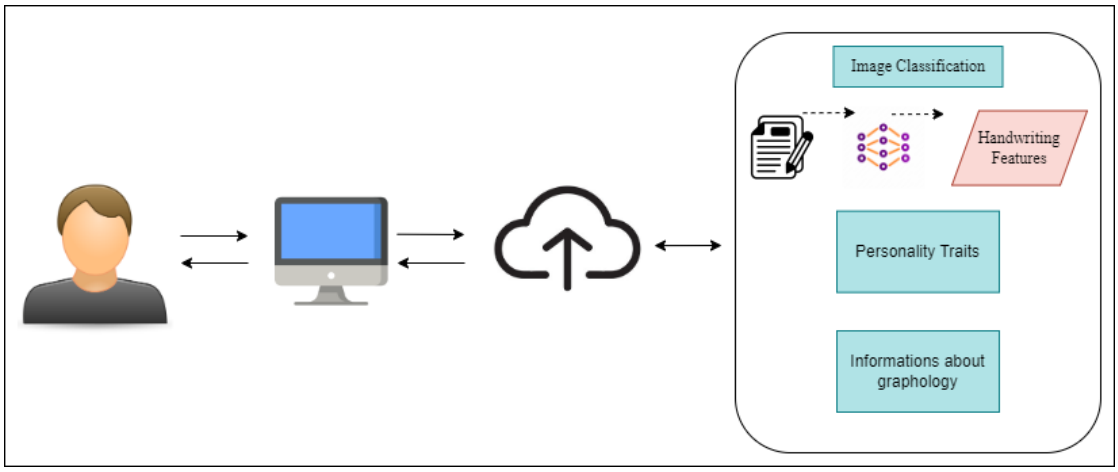


Figure 4. 2 System Architecture

4.2.2 User Interface Design

In the following section, we will dive into the details of the web application's design, which has been primarily crafted to incorporate the three modules outlined within the scope. The main user interface design is as Figure 4.3 below.

Figure 4. 3 UI Design

4.2.2.1 Navigation Design

In the design phase, navigation structure diagrams clearly demonstrate how the different interfaces are interconnected and how the user seamlessly transitions between them. Effective navigation design is paramount in shaping user interaction with the website.

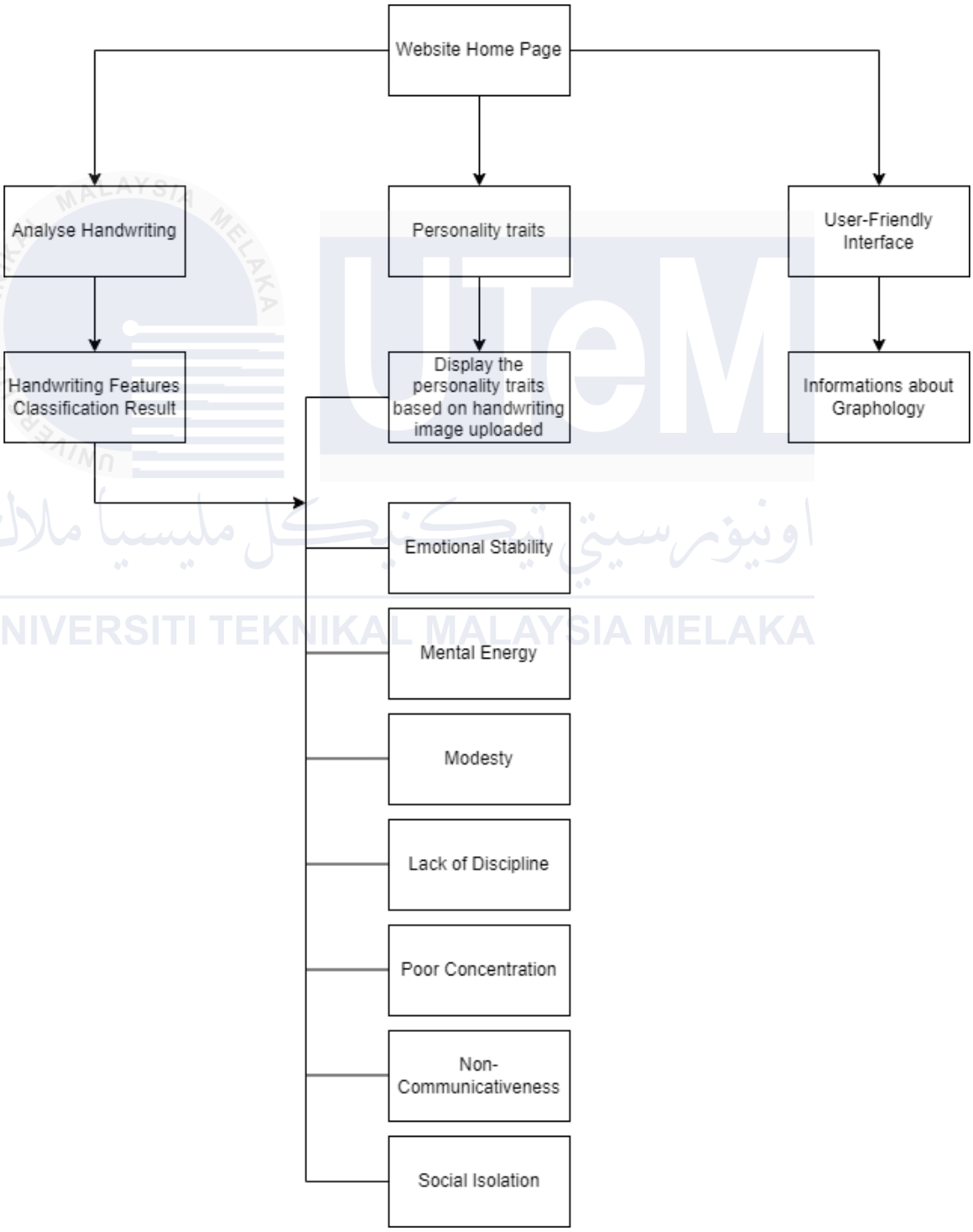


Figure 4. 4 Navigation Design

Figure 4.4 shows the navigation design of the AI-Based Handwriting Analysis System for the necessary module to be developed.

4.2.2.2 Input Design

This section discusses input design in the AI-Based Handwriting Analysis System. One module is involved in the input design for handwriting analysis classification.

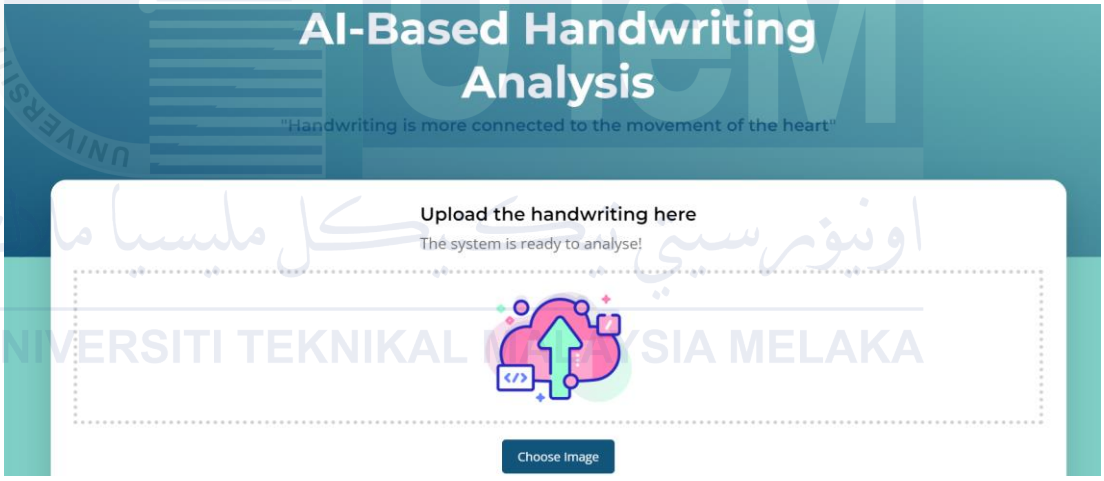


Figure 4. 5 Input Design for Module 1

In Figure 4.5 as above, that is the input design for the handwriting analyser classification module. To upload a handwriting image, users have the option to either click the 'Choose Image' button or the upload icon.

4.2.2.4 Output Design

This section will show the output design for each module:

i. Module 1: Interactive User Interface

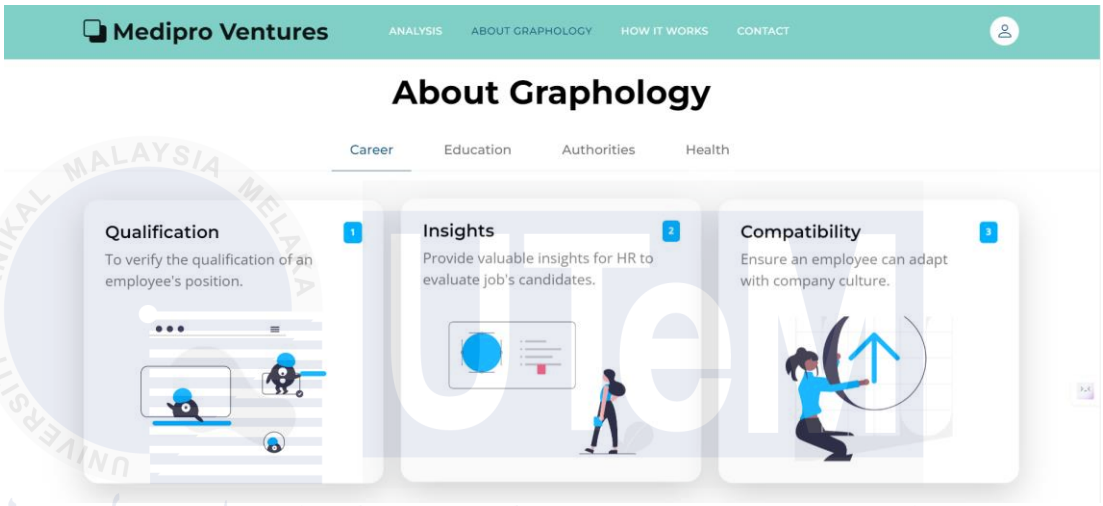


Figure 4. 4 About Graphology Dashboard

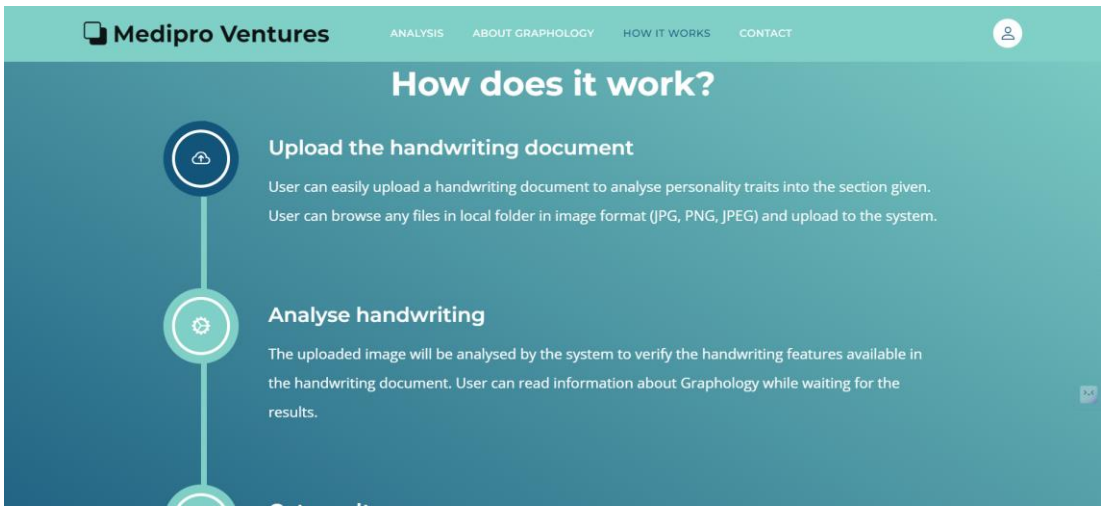


Figure 4. 5 How it works Dashboard

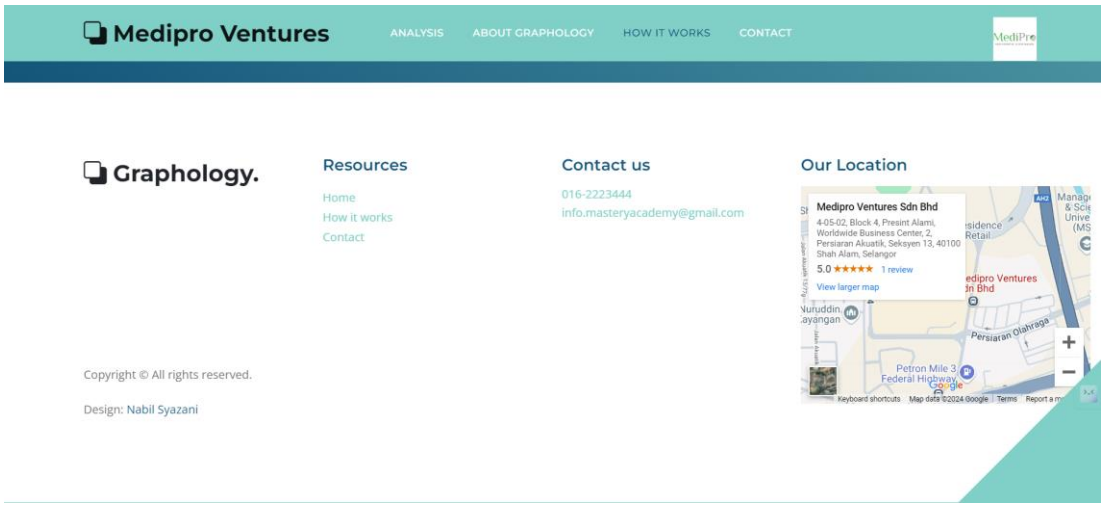


Figure 4. 6 End of Web Page

Figure 4.4 until 4.6 represents as the user interface that can give good user experience (UX) to the users. In Figure 4.4, the user can click the other choices to get information that relates the particular field with the graphology.

ii. Handwriting Analyser

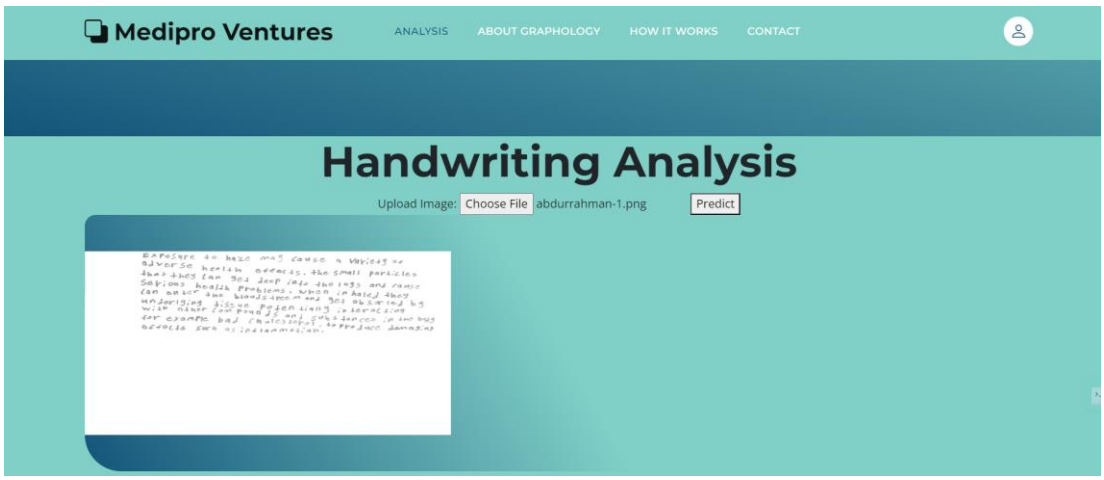


Figure 4. 7 Handwriting Analyser Page

Figure 4.7 above shows the handwriting analyser section where users may upload the handwriting image file that they want to analyse for the system to read the

image. Hence, after the image was uploaded into the system, the result of handwriting features will appear and be identified. The features can be referred to in Figure 4.8 below.

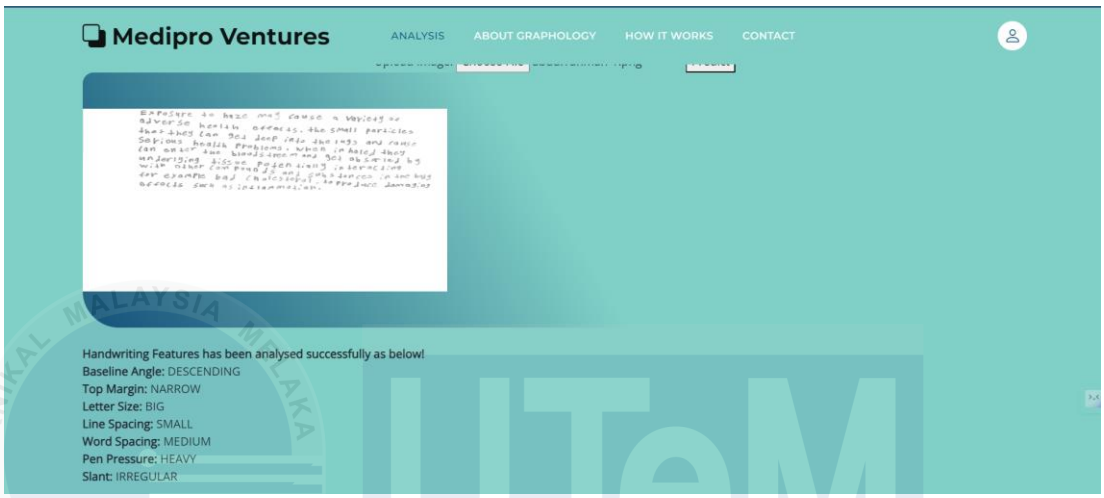


Figure 4. 8 Handwriting Features Output

After completing predictions and analysis on the uploaded handwriting image, a button called “Generate Report”, appears to generate an analysis report based on the personality and also handwriting features that combine them. Figures 4.9 and 4.10 below illustrate on how the generated PDF looks like and the functionality of the “Generate Report” button.

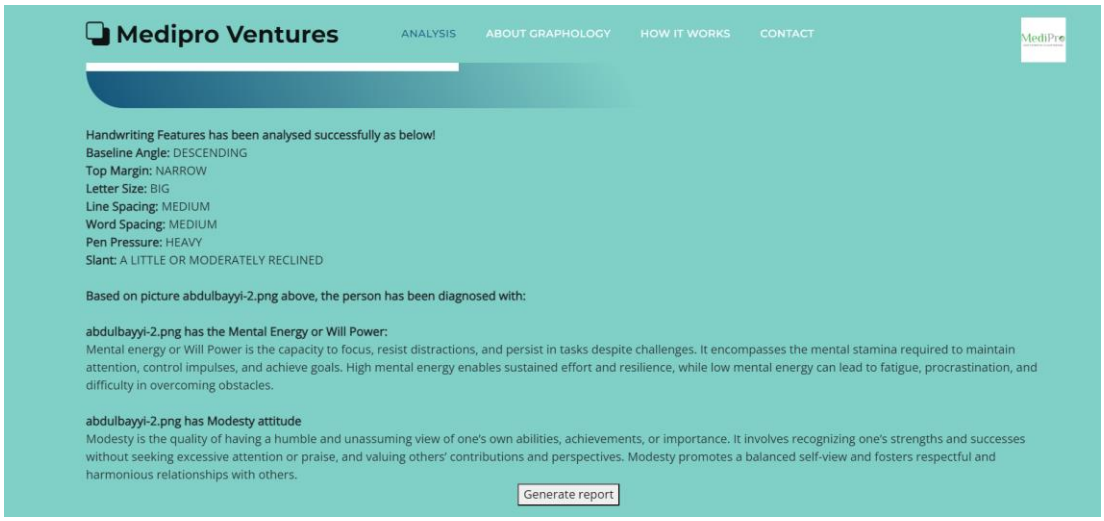


Figure 4. 9 Generate Report Button

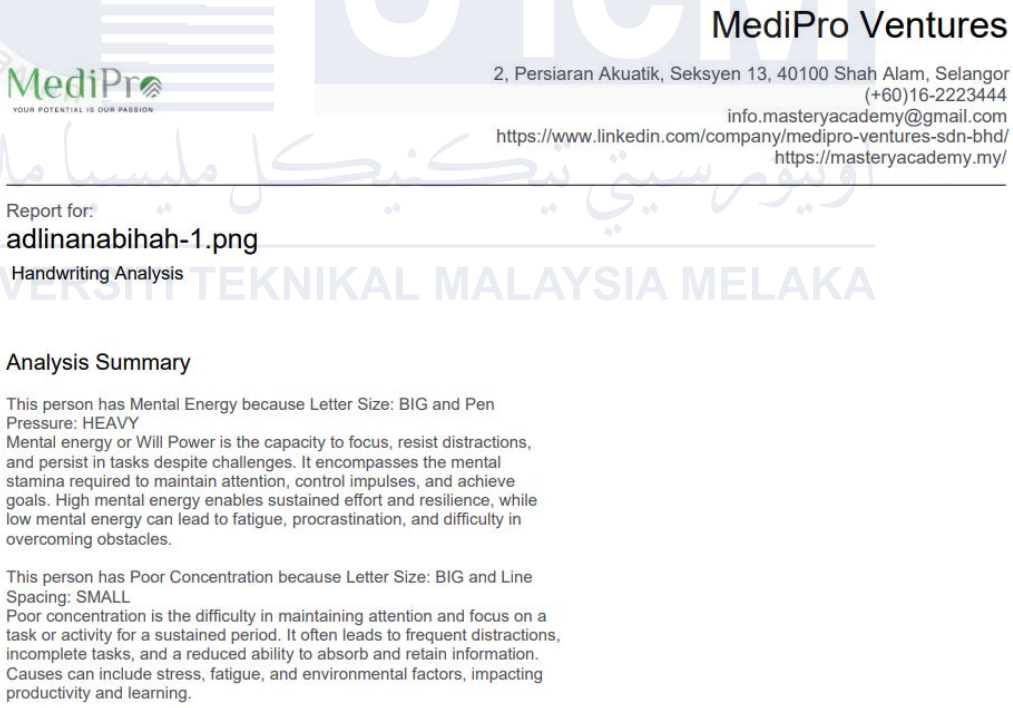


Figure 4. 10 Analysis Report Generated

iii. Personality Traits Recognition

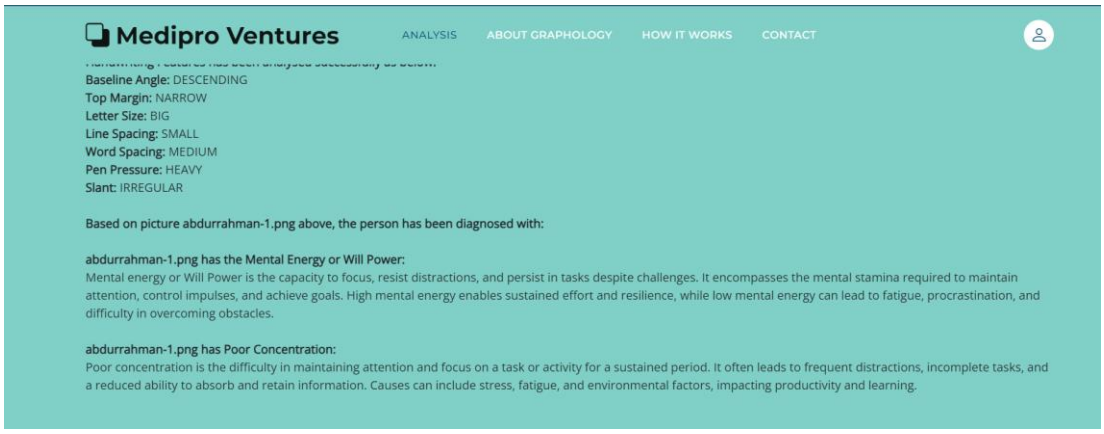


Figure 4. 11 Personality Traits Results

Figure 4.11 above illustrates the personality traits obtained from the uploaded handwriting image. Users only know the tendency of the personality traits. For example, out of eight personality traits, however, it only appears two because the person specifically diagnosed as for the two personalities.

4.2.3 Database Design

In this section, we will delve into the database design for project analysis. The database is structured using a folder system. Within the data folder, there are three subfolders, each subfolder contains images for training and testing purposes. These images primarily consist of handwritten documents. As a reference, Figure 4.12 below is for a visual representation of the design.

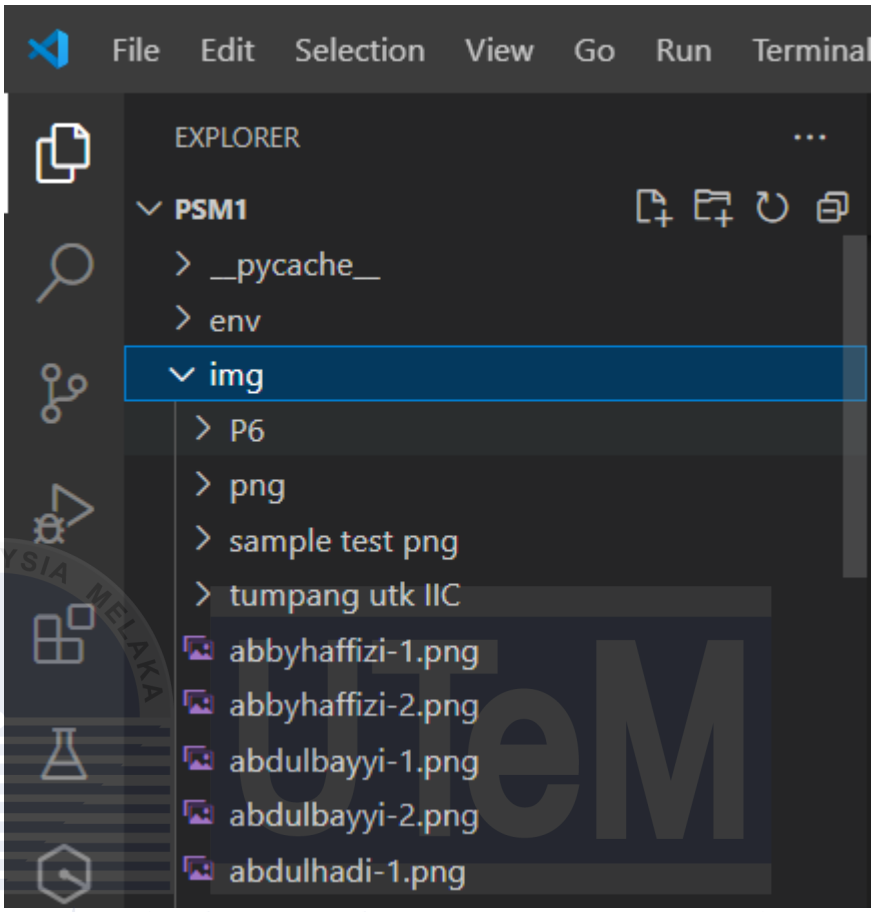


Figure 4. 12 Database Design

4.3 AI Component Design

This section illustrates AI component design that has been utilised in the project. There are two (2) AI techniques in AI-Based Handwriting Analysis which include Computer Vision and Machine Learning.

4.3.1 Computer Vision

AI-Based Handwriting Analysis is an innovative project that leverages advanced computer vision techniques to analyse handwriting and extract personality

traits from it. By examining various aspects of an individual's handwriting, such as the shape, size, and spacing of letters, this project aims to provide insights into the writer's personality characteristics. This comprehensive analysis involves several core computer vision techniques, each playing a crucial role in the process.

One of the key techniques used in this project is semantic segmentation. This method involves dividing an image of handwritten text into multiple segments or regions based on the semantic meaning of its content. Semantic segmentation makes it possible to precisely identify individual letters and their boundaries by giving each pixel a class label. This enables a thorough knowledge of the handwriting's structure. This level of detail-oriented examination is necessary to properly decipher the subtleties of the handwriting, which leads to the identification of significant personality attributes. Figure 4.13 illustrates how the image undergoes the image segmentation. Resizing and converting grayscale can be useful during image segmentation to improve the quality and accuracy of the resulting segments. Resizing involves adjusting the size of the image to a specific scale, which can be necessary to ensure that the algorithm properly identifies objects and edges within the image. Meanwhile, for the converting grayscale, it can help to reduce noise and artefacts in the image, making it easier to identify and isolate specific regions of interest. Additionally, some segmentation algorithms perform better when working with grayscale images, so converting the image to grayscale may be necessary to achieve the desired results.

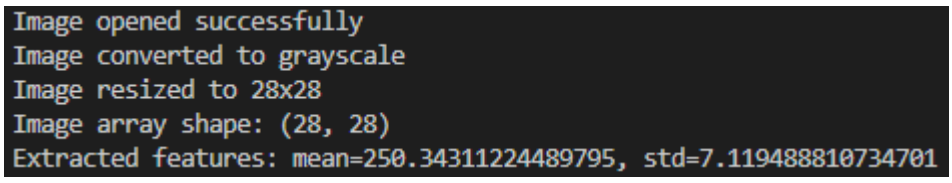


Figure 4. 13 Semantic segmentation

AI-Based Handwriting Analysis also uses image classification as a basic technique. In this case, image classification entails assigning distinct predetermined groupings or categories to every handwriting segment. The system learns to distinguish between various handwriting styles by using a dataset of labelled handwriting examples to train a machine learning model. This classification process

helps in identifying eight (8) key characteristics of the handwriting, such as baseline angle, top margin, letter size, line spacing, word spacing, pen pressure and slant angle, which are crucial indicators of personality traits. Figure 4.14 until 4.20 shows how the threshold value is crucial for every handwriting features.

```
def determine_baseline_angle(raw_baseline_angle):
    comment = ""
    # falling
    if(raw_baseline_angle >= 0.2):
        baseline_angle = 0
        comment = "DESCENDING"
    # rising
    elif(raw_baseline_angle <= -0.3):
        baseline_angle = 1
        comment = "ASCENDING"
    # straight
    else:
        baseline_angle = 2
        comment = "STRAIGHT"

    return baseline_angle, comment
```

Figure 4. 14 Baseline Angle Threshold Value

Figure 4.14 shows the baseline angle features and its threshold value.

```
def determine_top_margin(raw_top_margin):
    comment = ""
    # medium and bigger
    if(raw_top_margin >= 1.7):
        top_margin = 0
        comment = "MEDIUM OR BIGGER"
    # narrow
    else:
        top_margin = 1
        comment = "NARROW"

    return top_margin, comment
```

Figure 4. 15 Top Margin Threshold Value

Figure 4.15 shows the top margin features and its threshold value.

```python
def determine_letter_size(raw_letter_size):
    comment = ""
    # big
    if(raw_letter_size >= 18.0):
        letter_size = 0
        comment = "BIG"
    # small
    elif(raw_letter_size < 13.0):
        letter_size = 1
        comment = "SMALL"
    # medium
    else:
        letter_size = 2
        comment = "MEDIUM"

    return letter_size, comment
```

Figure 4. 16 Letter Size Threshold Value

Figure 4.16 shows the letter size features and its threshold value.

```python
def determine_line_spacing(raw_line_spacing):
    comment = ""
    # big
    if(raw_line_spacing >= 3.5):
        line_spacing = 0
        comment = "BIG"
    # small
    elif(raw_line_spacing < 2.0):
        line_spacing = 1
        comment = "SMALL"
    # medium
    else:
        line_spacing = 2
        comment = "MEDIUM"

    return line_spacing, comment
```

Figure 4. 17 Line Spacing Threshold Value

Figure 4.17 shows the line spacing features and its threshold value.

```python
def determine_word_spacing(raw_word_spacing):
    comment = ""
    # big
    if(raw_word_spacing > 2.0):
        word_spacing = 0
        comment = "BIG"
    # small
    elif(raw_word_spacing < 1.2):
        word_spacing = 1
        comment = "SMALL"
    # medium
    else:
        word_spacing = 2
        comment = "MEDIUM"

    return word_spacing, comment
```

Figure 4. 18 Word Spacing Threshold Value

Figure 4.18 shows the word spacing features and its threshold value.

```python
def determine_pen_pressure(raw_pen_pressure):
    comment = ""
    # heavy
    if(raw_pen_pressure > 180.0):
        pen_pressure = 0
        comment = "HEAVY"
    # light
    elif(raw_pen_pressure < 151.0):
        pen_pressure = 1
        comment = "LIGHT"
    # medium
    else:
        pen_pressure = 2
        comment = "MEDIUM"

    return pen_pressure, comment
```

Figure 4. 19 Pen Pressure Threshold Value

Figure 4.19 shows the pen pressure features and its threshold value.

```python
def determine_slant_angle(raw_slant_angle):
    comment = ""
    # extremely reclined
    if(raw_slant_angle == -45.0 or raw_slant_angle == -30.0):
        slant_angle = 0
        comment = "EXTREMELY RECLINED"
    # a little reclined or moderately reclined
    elif(raw_slant_angle == -15.0 or raw_slant_angle == -5.0 ):
        slant_angle = 1
        comment = "A LITTLE OR MODERATELY RECLINED"
    # a little inclined
    elif(raw_slant_angle == 5.0 or raw_slant_angle == 15.0 ):
        slant_angle = 2
        comment = "A LITTLE INCLINED"
    # moderately inclined
    elif(raw_slant_angle == 30.0 ):
        slant_angle = 3
        comment = "MODERATELY INCLINED"
    # extremely inclined
    elif(raw_slant_angle == 45.0 ):
        slant_angle = 4
        comment = "EXTREMELY INCLINED"
    # straight
    elif(raw_slant_angle == 0.0 ):
        slant_angle = 5
        comment = "STRAIGHT"
    # irregular
    else:
        slant_angle = 6
        comment = "IRREGULAR"

    return slant_angle, comment
```

Figure 4. 20 Slant Angle Threshold Value

Figure 4.20 shows the slant angle features and its threshold value.

Additionally, template matching is used to enhance the analysis process. This technique involves locating a sub-image, or template, within a larger image of handwriting. By comparing the template with different parts of the handwriting sample, template matching helps in detecting specific patterns and shapes that are consistent with certain personality traits. This method is particularly useful for identifying known handwriting features that correlate with psychological profiles.

4.3.2 Machine Learning

Machine learning models analyse data and identify patterns to make predictions about future events. Various types of machine learning models exist,

including supervised learning, unsupervised learning, and reinforcement learning, each with its own strengths and weaknesses. Supervised learning is commonly utilised for prediction tasks, as it enables the model to learn from labelled data and accurately predict future events based on this acquired knowledge. For this particular project, an appropriate model should be chosen to classify the handwriting images into each personality trait respectively. Hence, the Support Vector Machine (SVM) model was selected as the best model for this project.

Feature extraction is a crucial element in processing the SVM model in order to transform raw handwriting data into a set of measurable attributes. In this case, the process is closely related to the computer vision technique which includes processing of image classification, segmentation and template matching. The pre-trained models were loaded by 'pickle' into the application. The feature vectors have their own corresponding labels or classifiers to train the SVM model to obtain the personality traits. When a new handwriting image sample is uploaded, its features are extracted and transformed into a feature vector. Hence, this resulting the SVM model can use this feature vector to classify the handwriting image into its own corresponding personality traits that have been recognised from the individual's handwriting. In this project, there are eight (8) personality traits that become the measurement of the personality which are emotional stability, mental energy or willpower, personal harmony and flexibility, modesty, lack of discipline, poor concentration, non-communicativeness and social isolation. Moreover, the result of the prediction of the personality traits based on the features is represented as binary. This means that if the individual has the personality it represents 1. Meanwhile, if the person does not have the personality, it represents 0. Therefore, the feature extraction to classify each personality trait was set and is illustrated as Table 4.1.

Table 4. 1 Classifiers for each personality trait

Classifier for Personality Traits	Handwriting Features
Emotional Stability	baseline angle, slant angle
Mental Energy or Willpower	letter size, pen pressure
Personal Harmony and Flexibility	letter size, top margin

Modesty	line spacing, word spacing
Lack of discipline	slant angle, top margin
Poor Concentration	letter size, line spacing
Non-Communicativeness	letter size, word spacing
Social Isolation	line spacing, word spacing

Therefore, it is essential to extract features when preparing handwriting data for AI-based Handwriting Analysis. By extracting meaningful structural and statistical features, the SVM model can effectively differentiate between various personality traits or emotional states. This process guarantees that the model receives the most pertinent information, resulting in precise and dependable predictions.

4.4 Detailed Design

This section provides a detailed exploration of the system's design, emphasizing the implementation of the system and its subsystems as outlined in the previous two designs. It offers a thorough examination of the implementation of modules, providing a comprehensive overview of each module's logical structure and its interfaces for interacting with other modules. For the overview of the handwriting analysis design, Figure 4.21 is referred to as the process flow framework.

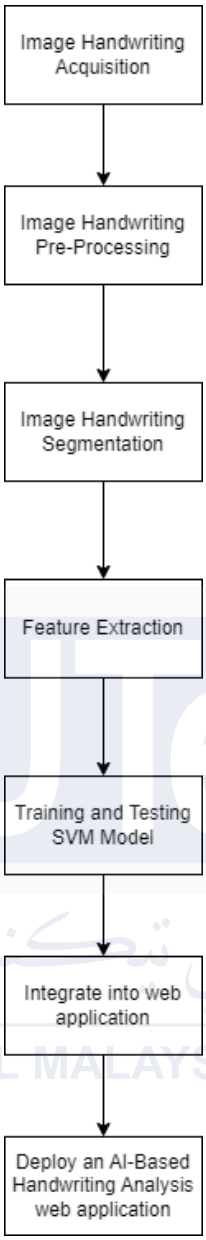


Figure 4. 21 Flowchart of Design

4.4.1 Software Design

Software design involves transforming user requirements into a form that enables the programmer to create and implement software. Figure 4.22 shows the software design of the system.

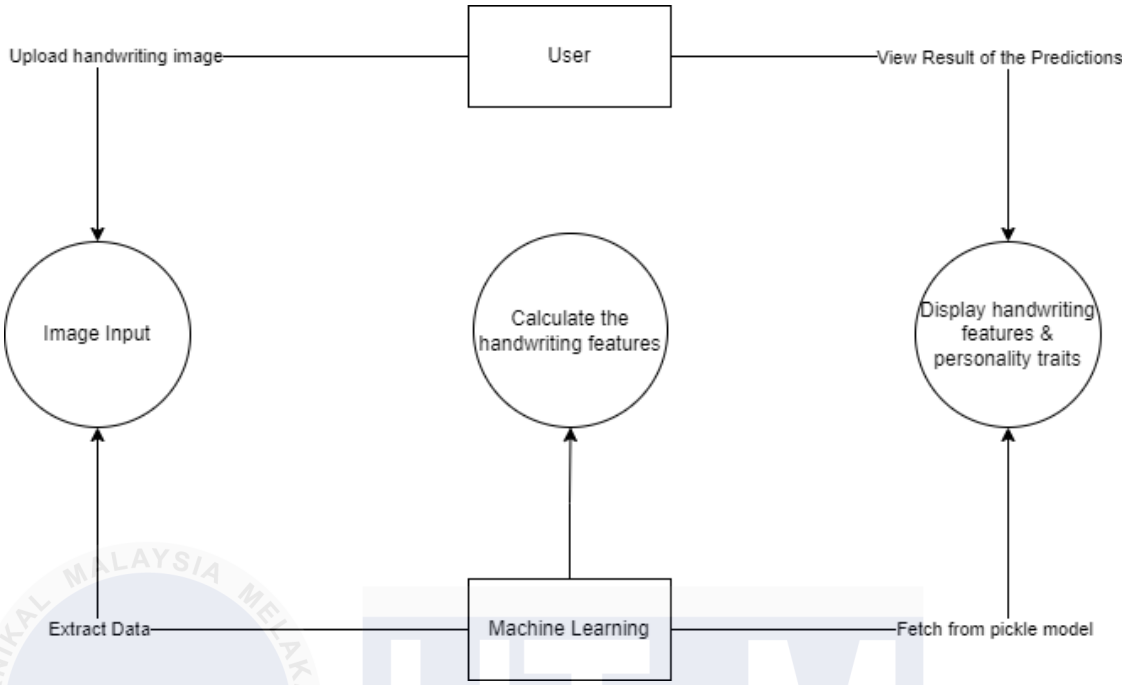


Figure 4. 22 Software Design

The diagram above depicts the implementation of the software design that ensures the smooth and accurate operation of the entire system.

4.5 Summary

This section provides a comprehensive overview of the system's design process and its intended functionality. The design phase is crucial for ensuring the smooth operation and successful accomplishment of the system's objectives. Our strategic approach involves developing interface designs for the three modules and their corresponding use case diagrams to provide the team with valuable insights into the system, ultimately leading to more efficient achievement of our goals. The subsequent chapter will delve into the results and discussion of the system's design.

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Introduction

This chapter presents the results and discussion of the AI-Based Handwriting Analysis system, focusing on its fulfilment of project requirements and overall performance. After implementation, we conducted a comprehensive testing process to ensure the system is bug-free and functions as intended. The system was tested on laptops with the developer handling the model evaluation. The testing was done by the graphologist, the domain expert and her team to provide expert feedback on the system's usability and effectiveness. Hence, clear roles and responsibilities are defined for the evaluation. The testing environment was carefully configured with the necessary software and hardware, including laptops and servers to ensure accurate results. For testing strategies, both black box and white box testing are utilised to evaluate the system's behaviour from an end-user perspective and assessing the internal structure and performance of the AI model. Performance metrics such as accuracy, precision, recall and F1-Score values were used to measure the model's effectiveness, ensuring a thorough and reliable assessment.

5.2 Evaluation of AI Techniques used in the project

In this project, the evaluation of AI techniques was concentrated on assessing the performance of prediction and classification, to obtain the robustness of the system. The system was specifically developed to analyze handwriting and accurately classify personality traits using a variety of AI methods. These methods included Support Vector Machines (SVM) for classification and advanced computer vision techniques such as semantic segmentation.

To ensure the prediction of the personality traits performance is smooth, a black box testing strategy was employed, which focuses on evaluating the system's behaviour and functionality from an end-user perspective without any knowledge of

the internal structure. This approach ensures that the system meets user expectations in the graphology scenarios. Meanwhile, when evaluating the model, the white box testing strategy was utilised, which requires a deep understanding of the model's internal workings to ensure its accuracy and reliability. The performance of each model using key metrics such as accuracy, precision, recall and F1-Score was evaluated to provide a comprehensive assessment of the system's ability to effectively and consistently classify personality traits based on the uploaded handwriting image. The elements of the performance evaluation vector can be found in Table 5.1, alongside with a remark of each element.

Table 5. 1 Performance Evaluation Metrics

Performance Evaluation Metrics	Remark
Accuracy	Epochs when the difference between validation and prediction accuracy is ±0.01
Precision	The standard of a positive prediction that the mode made
Recall	Evaluates the frequency with which a machine learning model accurately detects true positives
F1 Score	The harmonic mean of a classification model's recall and precision

5.2.1 Support Vector Machine

The performance of Support Vector Machine (SVM) models on different training and testing datasets is indicated by the results obtained. The main goal of SVM is to find the optimal hyperplane to effectively separate data points into different classes and maximize the margin between them. The accuracy, precision, recall, and F1 score are performance indicators used to evaluate how well the models are achieving this goal. Table 5.2 shows the results of scores across all the key metrics. Eight models were produced after training which include:

i. Model 1: Emotional Stability (baseline angle, slant angle)
ii. Model 2: Mental energy or willpower (letter size, pen pressure)
iii. Model 3: Modesty (letter size, top margin)
iv. Model 4: Personal harmony and flexibility (line spacing, word spacing)
v. Model 5: Lack of discipline (slant angle, top margin)
vi. Model 6: Poor concentration (letter size, line spacing)
vii. Model 7: Non-communicativeness (letter size, word spacing)
viii. Model 8: Social isolation (line spacing, word spacing)

Each model has their own handwriting features combination that produces personality traits. Hence, the scores for every model indicate the reliability of the system.

Table 5. 2 Result of SVM

Model	Metrics			
	Accuracy	Precision	Recall	F1-Score
1	1.0	1.0	1.0	1.0
2	1.0	1.0	1.0	1.0
3	1.0	1.0	1.0	1.0
4	1.0	1.0	1.0	1.0
5	0.94	0.89	0.94	0.92
6	1.0	1.0	1.0	1.0
7	1.0	1.0	1.0	1.0
8	1.0	1.0	1.0	1.0

The results for Models 1, 2, 3, 4, 6, 7, and 8 show perfect scores across all metrics, indicating flawless performance on the provided data. In the case of SVM, this suggests that each model's hyperplane perfectly separates the data points into their respective classes, with no classification errors. However, such perfect performance may indicate overfitting because the data for training and testing did not split perfectly. Overfitting happens when the model becomes too finely tuned to the

training data, including noise and outliers, which can result in poor generalization to new, unseen data.

On the other hand, Model 5 exhibits slightly lower performance, with an accuracy of approximately 95%, precision of 90%, recall of 95%, and an F1 score of 92%. This suggests that the SVM for Model 5 may have encountered more complex or overlapping class boundaries within its feature space, making it challenging to achieve perfect separation. The results imply that the optimal hyperplane identified by this model does not perfectly separate all data points, resulting in some misclassifications. However, these metrics indicate strong overall performance. Additionally, the slightly lower performance of Model 5 may be a positive indicator, suggesting that the model is less prone to overfitting and potentially better at generalizing to new data compared to other models.

While the majority of models achieve near-perfect scores, it's important to address the possibility of overfitting, which can lead to a poor generalization of the data. In contrast, Model 5 demonstrates a more balanced performance and may be better suited for practical applications due to its slightly lower yet still impressive results. By expanding the dataset size, it could help prevent overfitting and enable the models to learn more generalized patterns.

5.2.2 Image classification

The AI-Based Handwriting Analysis system uses computer vision techniques to accurately classify handwriting features and derive personality traits. Firstly, it involves categorizing each image or segment of the handwriting sample into predefined classes that correspond to specific handwriting features or characteristics. Each handwriting feature has their own calculation to classify the feature respectively. This classification process is necessary because it helps the system to identify and differentiate between various handwriting features, which can indicate the writer's personality. To achieve this classification, a machine learning model is trained on a labeled dataset. This allows the model to recognize patterns and features associated with different handwriting traits.

The process involves extracting particular handwriting features from the classified images. This includes analysing each segment of the handwriting to identify and measure key characteristics, such as letter shapes, word spacing, and the height of t-bars. These features are then stored in a list, creating a structured representation of the handwriting. The extraction step is essential in this system as it converts raw image data into valuable information for personality trait analysis. The accuracy of the personality predictions is directly impacted by the quality and precision of the extracted features.

The AI-Based Handwriting Analysis system combines image classification and feature extraction to comprehensively and accurately analyse handwriting samples. The system utilizes 'categorized.py' to classify handwriting features and 'extract.py' for detailed feature extraction, effectively mapping these features to personality traits.

5.3 Testing of Functional Requirement

This section provides an overview of the testing process for the system's functional requirements. It includes the identification of test cases, the assignment of testers, and the results of each test case, indicating whether the result can be a success or failure. This ensures that all key functionalities of the AI-Based Handwriting Analysis system operate as intended and meet the specified project requirements.

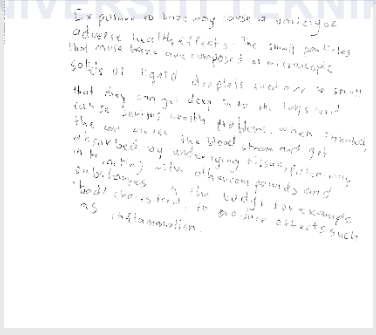
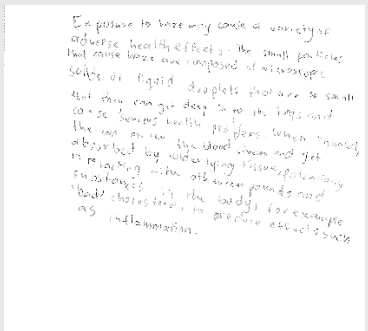
5.3.1 Test Case for Image Testing

The test scenario is to check the output of a handwriting image for each handwriting features to produce personality trait prediction results. Three different images are used in this test case to test the SVM model. Therefore, in order to complete this test case, a handwriting image was uploaded to the system. The expected outcome is the result that should match the handwriting features. The two combinations of handwriting features can generate the eight personalities respectively. The corresponding match is as follows:

i. Emotional stability: baseline angle, slant angle
ii. Mental energy or willpower: letter size, pen pressure
iii. Modesty: letter size, top margin
iv. Personal harmony and flexibility: line spacing, word spacing
v. Lack of discipline: slant angle, top margin
vi. Poor concentration: letter size, line spacing
vii. Non-communicativeness: letter size, word spacing
viii. Social isolation: line spacing, word spacing

Table 5.3 until 5.10 shows the test case table for each handwriting feature to match the personality traits. If the expected result matches with the handwriting feature, the result is success. If it is vice versa, then the result is fail.

Table 5. 3 Baseline Angle

Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Ascending/Descending Personality: Emotional Stability	Characteristic: Descending Personality: None	Pass
	Characteristics: Ascending/Descending Personality: Emotional Stability	Characteristic: Descending Personality: None	Pass
	Characteristics:	Characteristic:	Pass

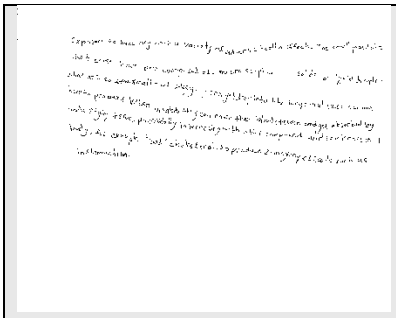
	Ascending/Descending, Personality: Emotional Stability	Descending, Personality: None	

Table 5. 4 Top Margin

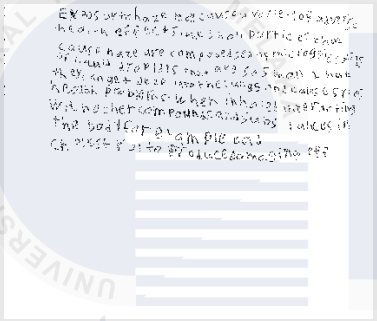
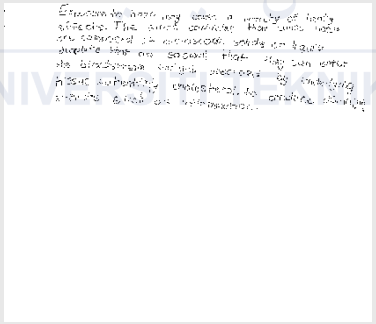
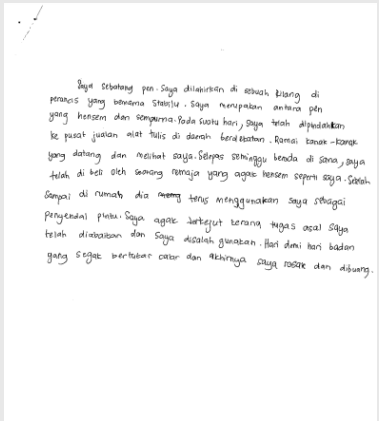
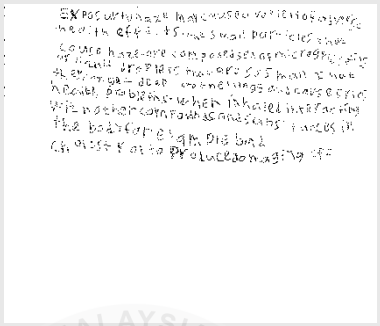
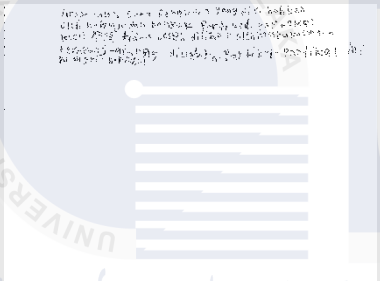
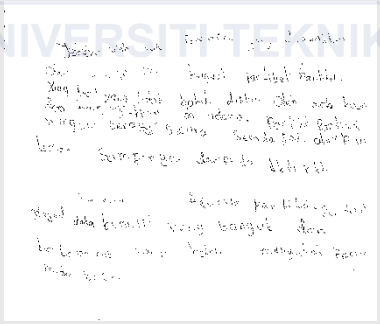
Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Narrow/Medium/Bigger Personality: Modesty/Lack of Discipline	Characteristic: Narrow Personality: None	Pass
	Characteristics: Narrow/Medium/Bigger Personality: Modesty/Lack of Discipline	Characteristic: Narrow Personality: None	Pass
	Characteristics: Narrow/Medium/Bigger Personality: Modesty/Lack of Discipline	Characteristic: Bigger Personality: None	Pass

Table 5. 5 Letter Size

Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Big/Small Personality: Mental energy or willpower/Modesty/Poor concentration/Non-communicativeness	Characteristic : Big Personality: poor concentration	Pass
	Characteristics: Big/Small Personality: Mental energy or willpower/Modesty/Poor concentration/Non-communicativeness	Characteristic : Small, Personality: Mental energy or willpower, non-communicativeness	Pass
	Characteristics: Big/Small Personality: Mental energy or willpower/Modesty/Poor concentration/Non-communicativeness	Characteristic : Big Personality: None	Fail

As shown in Table 5.5, the third data encounter failure. This is because the data is not clear and blurry. Additionally, the personality traits also cannot be determined since it is blurry. Fortunately, the system can still obtain the handwriting feature which is the letter size despite of having difficulties in analysing the personality traits.

Table 5. 6 Line Spacing

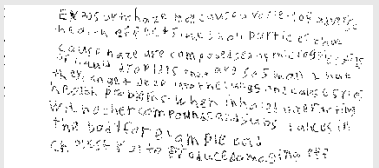
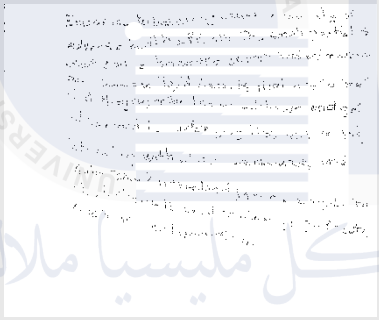
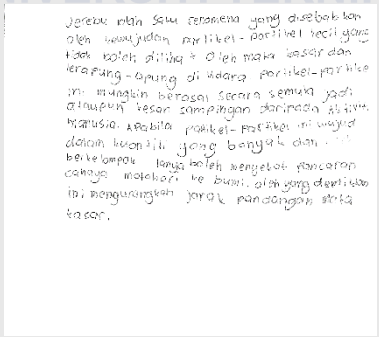
Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Big/Small/Medium Personality: Personal harmony and flexibility/Poor concentration/Social isolation	Characteristic: Small Personality: Poor concentration	Pass
	Characteristics: Big/Small/Medium Personality: Personal harmony and flexibility/Poor concentration/Social isolation	Characteristic: Big Personality: Social isolation	Pass
	Characteristics: Big/Small/Medium Personality: Personal harmony and flexibility/Poor concentration/Social isolation	Characteristic: Medium Personality: None	Pass

Table 5. 7 Word Spacing

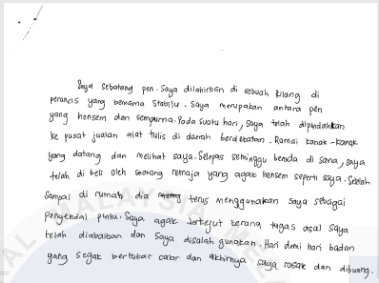
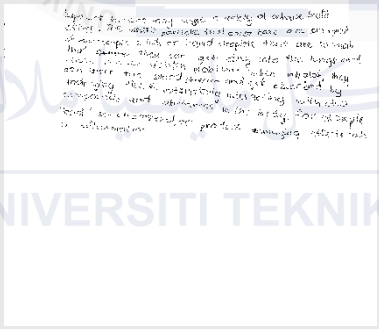
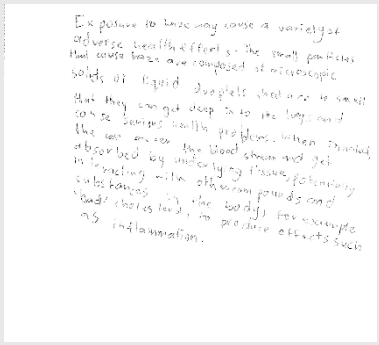
Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Big/Small/Medium Personality: Personal harmony and flexibility/Non-communicativeness/ Social isolation	Characteristic: Medium Personality: Personal harmony and flexibility, Social isolation	Pass
	Characteristics: Big/Small/Medium Personality: Personal harmony and flexibility/Non-communicativeness/ Social isolation	Characteristic: Small Personality: None	Pass
	Characteristics: Big/Small/Medium Personality: Personal harmony and flexibility/Non-communicativeness/ Social isolation	Characteristic: Big Personality: Social isolation	Pass

Table 5. 8 Pen Pressure

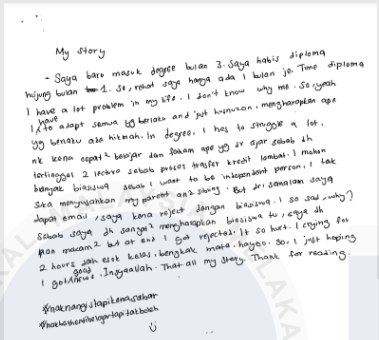
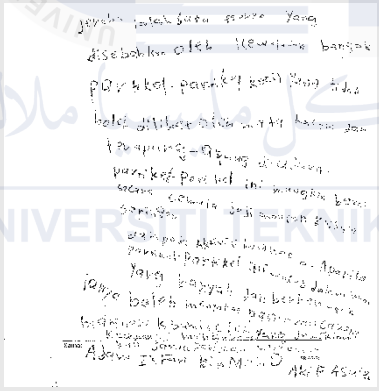
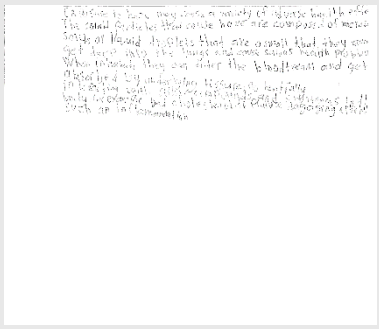
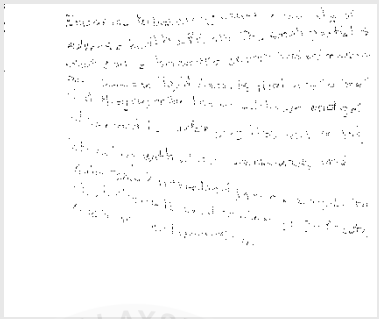
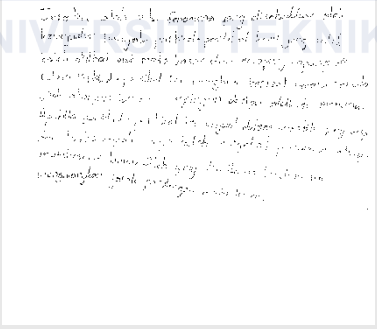
Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Heavy/Light/Medium Personality: Mental energy or willpower	Characteristic: Medium Personality: Mental energy or willpower	Pass
	Characteristics: Heavy/Light/Medium Personality: Mental energy or willpower	Characteristic: Heavy Personality: Mental energy or willpower	Pass
	Characteristics: Heavy/Light/Medium Personality: Mental energy or willpower	Characteristic: Light Personality: Mental energy or willpower	Pass

Table 5. 9 Slant Angle

Test Data	Expected Outcome	Actual Result	Status (Pass/Fail)
	Characteristics: Extremely reclined/Moderately reclined/Little inclined/Moderately inclined/Extremely inclined/Straight/Irregular Personality: Emotional stability/Lack of discipline	Characteristic: Moderately reclined Personality: None	Pass
	Characteristics: Extremely reclined/Moderately reclined/Little inclined/Moderately inclined/Extremely inclined/Straight/Irregular Personality: Emotional stability/Lack of discipline	Characteristic: Irregular Personality: None	Pass
	Characteristics: Extremely reclined/Moderately reclined/Little inclined/Moderately inclined/Extremely inclined/Straight/Irregular Personality: Emotional stability/Lack of discipline	Characteristic: Little inclined Personality: None	Pass

According to the result, each handwriting features are classified accurately based on the images uploaded. The “None” for the personality represents that the person has other personalities instead of the personality assigned to each handwriting feature respectively. The actual result shows that this image testing has been successfully tested and passed. The actual result matches with the characteristics of the handwriting features, which produce personality traits for each of them.

5.3.2 Test Case for Website Testing

The test case for each web application module is significant to ensure the implementation of each module is a success. To achieve the primary objectives, this website should be an AI-driven web application. Each test case includes the test number, test action, expected output, and test status. The test step details the steps needed to execute the test, such as the action and the data. Additionally, the test result indicates whether the test failed or passed. Table 5.10 until 5.12 shows each test case detailed documentation.

Test Case ID: 01

Interface: Handwriting Analysis

Operation: Upload an image and view the result of the prediction

Table 5. 10 Test Case 01

Test Case ID	Action	Expected Outcome	Status
01A	Click ‘Choose file’ button and choose a handwriting image	Picture display in the section	Pass
01B	Click ‘Predict’ button after choosing image	Loading while waiting for the result	Pass
01C	View result of prediction below image	Load the result of prediction of handwriting features and personality traits	Pass
01D	Click ‘Generate Report’ button	A generated analysis report will be downloaded automatically	Pass

Test Case ID: 02

Interface: About Graphology

Operation: View information about graphology

Table 5. 11 Test Case 02

Test Case ID	Action	Expected Outcome	Status
02A	Click button ‘About Graphology’ in the top bar list	Load to About Graphology section	Pass
02B	Click any button in the top bar list of the section	Display information about graphology based on the button chosen	Pass
02C	Explore the top bar list	Load to the selected section	Pass

Test Case ID: 03

Interface: Graphology

Operation: Contact phone number, email, and location (Google Maps)

Table 5. 12 Test Case 03

Test Case ID	Action	Expected Outcome	Status
03A	Click the number phone attached	Link to a call log app	Pass

03B	Click the email attached	Link to favourite email, proceeding to compose an email	Pass
03C	Click the maps attached	Link to Google Maps	Pass
03D	Click ‘Graphology’ button	Redirect to handwriting analysis section	Pass

The system has successfully passed all test cases for matching handwriting features to personality traits. This demonstrates that the system accurately identifies and classifies the features as intended. The results confirm that the functional requirements for this feature are fully met. No critical issues were encountered, and the system is now ready for deployment. Any minor issues identified will be addressed in future improvements time by time

.

5.4 Summary

In this chapter, a comprehensive overview of the results and discussions covers the testing process for the AI-based handwriting analysis system, specifically emphasizing the verification of functional requirements. Through a series of test cases, the system's capability was assessed to accurately match handwriting features to personality traits. The results successfully demonstrate that the system fulfils the specified objectives. The following chapter will serve to wrap up the project as a whole.

CHAPTER 6: CONCLUSION

6.1 Observation on Weaknesses and Strengths

This project has its own weaknesses and strengths, as any project that has been done. The project analysis's weaknesses and strengths are covered in this section. The system's success is demonstrated by its strengths, and future improvement opportunities are indicated by its limitations and weaknesses.

6.1.1 Strengths

The AI-based Handwriting Analysis System introduces an innovative solution for personality assessment by automating a traditionally manual process, ensuring more consistent and objective results. Users may upload a handwriting image to determine the characteristics of a person quickly. Through a combination of significant testing strategies, the project underwent comprehensive evaluation from both end-user and technical perspectives, enhancing reliability and accuracy. User-centric design principles guided the development of an intuitive and user-friendly interface, specifically catered to graphologists like the domain experts who assist in this project and her teams, enabling efficient utilisation of the tool in their work. Leveraging robust AI techniques such as semantic segmentation, template matching, and SVM classification further enhances the system's capability to accurately identify personality traits from handwriting. Additionally, since the system can generate an analysis report automatically, the user can download it to the computer as well. Therefore, it can reduce the workload and maximise user experience, either aimed for the company use or for client use.

6.1.2 Weaknesses

The effectiveness of the AI model greatly depends on the quality and diversity of the training data. The limited datasets collected can be exposed to a risk of the model's ability to make accurate predictions. Moreover, the handwriting image must be written on blank paper and use a ball pen to get an accurate result. Even though the analysis is automated, an expert interpretation like the domain expert from Medipro Ventures was indeed needed, particularly in cases where the AI's predictions are unclear. Additionally, the current system also can only focus on predicting eight personality traits which are emotional stability, mental energy or will power, modesty, personal harmony and flexibility, lack of discipline, poor concentration, non-communicativeness and social isolation. Implementing and integrating different AI techniques such as image classification and feature extraction can present technical challenges that require significant computational resources.

6.2 Proposition for Improvement

To enhance the AI-Based Handwriting Analysis system there are a few enhancements that can be implemented. Initially, the existing system focuses on eight personality traits, which restricts its effectiveness. By broadening the range of personality traits, a thorough evaluation can be achieved, offering deeper insights into an individual’s characteristics. Next, it is essential to automate a dashboard that can track the traffic of analysed users for each category of personality traits. To further increase the tool's versatility and ease of use, the system should be improved to accept any image of handwriting without requiring compliance with any particular rules. The system's overall efficiency would be increased if more handwriting features beyond the existing six; baseline angle, top margin, letter size, line spacing, word spacing and pen pressure, were examined. This would result in more precise and in-depth personality predictions.

6.3 Project Contribution

This project specifically contributes to Medipro Ventures Sdn. Bhd. by introducing an advanced AI-Based Handwriting Analysis system that enhances the efficiency and accuracy of personality assessments. By automating the analysis process, the system reduces the time and effort required for manual evaluations, allowing graphologists such as the domain expert and her team to focus on more complex tasks. Moreover, the tool standardizes results, minimizing biases and inconsistencies that obtain from human error. Additionally, this project has the potential to expand in the real industry market. With the inclusion of additional personality traits and handwriting features, this project will be fit enough in position to be commercialised and for the company's use as well.

6.4 Summary

The AI-based Handwriting Analysis system developed in this project effectively fulfils its primary objectives by identifying handwriting features using computer vision, building a machine learning-based analysis model for handwriting, and enhancing the accuracy of personality assessments. Instead of traditionally manual tasks, the system significantly improves work efficiency for graphologists such as the domain expert from Medipro Ventures Sdn. Bhd and her team. Its design and implementation align with the project’s goals of delivering a robust, user-friendly tool while also having the potential for future expansion. Despite of planning of a further enhancement, such as adding more personality traits and handwriting features, the project conclusively achieves its intended outcomes and provides a solid foundation for future improvements.

REFERENCES

Digital Scientists. (2024). *Handwriting Analysis | AI + Machine Learning | Digital Scientists*. [online] Available at: https://digitalscientists.com/case-studies/handwriting-analysis/

Kim, H.G. (2022). *Personality Prediction System Based on Graphology using Machine Learning*. [online] Medium. Available at: https://grantkim94.medium.com/personality-prediction-system-based-on-graphology-using-machine-learning-929fdbae0dee.

Kniazieva, Y. (2022). *AI Handwriting Recognition*. [online] labelyourdata.com. Available at: https://labelyourdata.com/articles/ai-handwriting-recognition.

Elngar, A.A., Jain, N., Sharma, D., Negi, H., Trehan, A. and Srivastava, A. (2020). A Deep Learning Based Analysis of the Big Five Personality Traits from Handwriting Samples Using Image Processing. *Journal of Information Technology Management*, 12(1), pp.3–35. doi:https://doi.org/10.22059/jitm.2020.78884.

Abdellatif Gahmousse, Rabeb Yousfi and Chawki Djeddi (2022). Handwriting Based Personality Traits Identification Using Adaptive Boosting and Textural Features. Communications in computer and information science, pp.216–227. doi:https://doi.org/10.1007/978-3-031-04112-9_16.

Hemlata, H., Manoj, M. and Kumar, S. (2018). Personality Detection using Handwriting Analysis Review. *Seventh International Conference on Advances in*

Computing Electronics and Communication ACEC2018. [online] doi:https://doi.org/10.15224/978-1-63248-157-3-33.

Sajeevan, S. and Wickramaarachchi, W.U. (2021). Detection of Personality Traits Through Handwriting Analysis Using Machine Learning Approach. *Advances on Smart and Soft Computing*, pp.79–89. doi:https://doi.org/10.1007/978-981-16-5559-3_8.

Mekhaznia, T., Djeddi, C. and Sarkar, S. (2021). Personality Traits Identification Through Handwriting Analysis. *Pattern Recognition and Artificial Intelligence*, pp.155–169. doi:https://doi.org/10.1007/978-3-030-71804-6_12.

Gupta, R., Mehrotra, D., Redouane Bouhamoum, Maroua Masmoudi and Hajer Baazaoui (2023). Handwriting Analysis AI-Based System for Assisting People with Dysgraphia. *Lecture Notes in Computer Science*, pp.185–199. doi:https://doi.org/10.1007/978-3-031-36024-4_14.

Chaubey, G. and Arjaria, S.K. (2021). Personality Prediction Through Handwriting Analysis Using Convolutional Neural Networks. *Proceedings of International Conference on Computational Intelligence*, pp.59–70. doi:https://doi.org/10.1007/978-981-16-3802-2_5.

Rahman, A.U. and Halim, Z. (2022). Predicting the big five personality traits from hand-written text features through semi-supervised learning. *Multimedia Tools and Applications*. doi:https://doi.org/10.1007/s11042-022-13114-5.

Samsuryadi, U., Kurniawan, R., Supardi, J., Sukemi, U. and Mohamad, F.S. (2023). A Framework for Determining the Big Five Personality Traits Using Machine

Learning Classification through Graphology. *Journal of Electrical and Computer Engineering*, [online] 2023, p.e1249004. doi:https://doi.org/10.1155/2023/1249004.

Rahman, A.U. and Halim, Z. (2022). Identifying dominant emotional state using handwriting and drawing samples by fusing features. *Applied Intelligence*. doi:https://doi.org/10.1007/s10489-022-03552-x.

M. Topaloglu and S. Ekmekci, (2017). Gender detection and identifying one's handwriting with handwriting analysis, *Expert Systems with Applications*, vol. 79, pp. 236–243.

Lauer, F., Suen, C.Y. and Bloch, G. (2007) 'A trainable feature extractor for handwritten digit recognition,' *Pattern Recognition*, 40(6), pp. 1816–1824. https://doi.org/10.1016/j.patcog.2006.10.011.

Lemos, N. *et al.* (2018) *Personality Prediction based on Handwriting using Machine Learning*. https://www.semanticscholar.org/paper/Personality-Prediction-based-on-Handwriting-using-Lemos-Shah/bde027c92fe9474bde6ac092e68bba40519f51a5.

Siddiqui, S., Khan, M. A., & Abulaish, M. (2021). Personality Traits Recognition Using Handwriting Analysis and Machine Learning. International Journal of Interactive Multimedia and Artificial Intelligence, 7(3), 14-21.

Lareki, A., Hafidi, M., El Ansari, N., & Moussaid, A. (2019). Artificial Neural Network-Based Personality Traits Classification Using Handwriting Analysis. International Journal of Advanced Computer Science and Applications, 10(5), 84-90.

Kanchan, M., Shetty, D., & G. K., M. (2020). Hybrid machine learning approach for personality prediction from handwriting. In Proceedings of the 2020 International

Conference on Computational Science and Computational Intelligence (CSCI), pp. 131

Fernandes, A. C., Coutinho, P., & Carneiro, D. (2019). Personality trait recognition using handwriting analysis and machine learning. In 2019 International Conference on Intelligent Systems (IS) (pp. 100- 105). IEEE.

Sati, K. and Kumar, D. (2023) 'Identifying the personality traits based on handwriting using ANN and MLP concept,' *Proceedings of the International Conference on Sustainable Computing and Smart Systems (ICSCSS 2023)* [Preprint]. https://doi.org/10.1109/icscss57650.2023.10169354.

Nagar, S. *et al.* (2018) *Personality Prediction based on Handwriting using Machine Learning*. journal-article.

Lamghari, N. *et al.* (2016) *Template matching for recognition of handwritten Arabic characters using structural characteristics and Freeman code, International Journal of Computer Network and Information Security*. journal-article. https://www.researchgate.net/publication/312087970.

APPENDICES

APPENDIX A: SOURCE CODE

Import Python Class

```
from flask import Flask, request, jsonify, render_template, send_file
import io
import joblib
import numpy as np
from PIL import Image
import extract
import categorize
import os

##bil
import os
import itertools
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_predict
import sklearn.metrics as metrics
from sklearn.metrics import accuracy_score
from mlxtend.plotting import plot_decision_regions
import matplotlib.pyplot as plt
import extract
import categorize
import joblib
```

Determine personality within handwriting features

```
# non communicativeness
X_t7 = []
for a, b in zip(X_letter_size, X_word_spacing):
    X_t7.append([a, b])

# social isolation
X_t8 = []
for a, b in zip(X_line_spacing, X_word_spacing):
    X_t8.append([a, b])
```

```python
# emotional stability
X_t1 = []
for a, b in zip(X_baseline_angle, X_slant_angle):
    X_t1.append([a, b])

# mental energy or will power
X_t2 = []
for a, b in zip(X_letter_size, X_pen_pressure):
    X_t2.append([a, b])

# modesty
X_t3 = []
for a, b in zip(X_letter_size, X_top_margin):
    X_t3.append([a, b])

# personal harmony and flexibility
X_t4 = []
for a, b in zip(X_line_spacing, X_word_spacing):
    X_t4.append([a, b])

# lack of discipline
X_t5 = []
for a, b in zip(X_slant_angle, X_top_margin):
    X_t5.append([a, b])

# poor concentration
X_t6 = []
for a, b in zip(X_letter_size, X_line_spacing):
    X_t6.append([a, b])
```

Determine the handwriting features

```python
def determine_baseline_angle(raw_baseline_angle):
    comment = ""
    # falling
    if(raw_baseline_angle >= 0.2):
        baseline_angle = 0
        comment = "DESCENDING"
    # rising
    elif(raw_baseline_angle <= -0.1):
        baseline_angle = 1
        comment = "ASCENDING"
    # straight
    else:
        baseline_angle = 2
        comment = "STRAIGHT"

    return baseline_angle, comment

def determine_top_margin(raw_top_margin):
    comment = ""
    # medium and bigger
    if(raw_top_margin >= 1.7):
        top_margin = 0
        comment = "MEDIUM OR BIGGER"
    # narrow
    else:
        top_margin = 1
        comment = "NARROW"

    return top_margin, comment
```

```python
def determine_letter_size(raw_letter_size):
    comment = ""
    # big
    if(raw_letter_size >= 18.0):
        letter_size = 0
        comment = "BIG"
    # small
    elif(raw_letter_size < 13.0):
        letter_size = 1
        comment = "SMALL"
    # medium
    else:
        letter_size = 2
        comment = "MEDIUM"

    return letter_size, comment

def determine_line_spacing(raw_line_spacing):
    comment = ""
    # big
    if(raw_line_spacing >= 3.5):
        line_spacing = 0
        comment = "BIG"
    # small
    elif(raw_line_spacing < 2.0):
        line_spacing = 1
        comment = "SMALL"
    # medium
    else:
        line_spacing = 2
        comment = "MEDIUM"

    return line_spacing, comment
```

```python
def determine_word_spacing(raw_word_spacing):
    comment = ""
    # big
    if(raw_word_spacing > 2.0):
        word_spacing = 0
        comment = "BIG"
    # small
    elif(raw_word_spacing < 1.2):
        word_spacing = 1
        comment = "SMALL"
    # medium
    else:
        word_spacing = 2
        comment = "MEDIUM"

    return word_spacing, comment

def determine_pen_pressure(raw_pen_pressure):
    comment = ""
    # heavy
    if(raw_pen_pressure > 180.0):
        pen_pressure = 0
        comment = "HEAVY"
    # light
    elif(raw_pen_pressure < 151.0):
        pen_pressure = 1
        comment = "LIGHT"
    # medium
    else:
        pen_pressure = 2
        comment = "MEDIUM"

    return pen_pressure, comment
```

```python
def determine_slant_angle(raw_slant_angle):
    comment = ""
    # extremely reclined
    if(raw_slant_angle == -45.0 or raw_slant_angle == -30.0):
        slant_angle = 0
        comment = "EXTREMELY RECLINED"
    # a little reclined or moderately reclined
    elif(raw_slant_angle == -15.0 or raw_slant_angle == -5.0 ):
        slant_angle = 1
        comment = "A LITTLE OR MODERATELY RECLINED"
    # a little inclined
    elif(raw_slant_angle == 5.0 or raw_slant_angle == 15.0 ):
        slant_angle = 2
        comment = "A LITTLE INCLINED"
    # moderately inclined
    elif(raw_slant_angle == 30.0 ):
        slant_angle = 3
        comment = "MODERATELY INCLINED"
    # extremely inclined
    elif(raw_slant_angle == 45.0 ):
        slant_angle = 4
        comment = "EXTREMELY INCLINED"
    # straight
    elif(raw_slant_angle == 0.0 ):
        slant_angle = 5
        comment = "STRAIGHT"
    # irregular
    else:
        slant_angle = 6
        comment = "IRREGULAR"

    return slant_angle, comment
```

Embed Google Maps

```html
<!-- Map Section -->
<div class="col-lg-3 col-md-4 col-6 mb-4 mb-lg-0">
    <h6 class="site-footer-title mb-3">Our Location</h6>
    <div class="map-container" style="height: 200px;">
        <iframe
            src="https://www.google.com/maps/embed?pb=!1m18!1m12!1m3!1d3984.069184495781 4!2d101.54704594024177!3d3.076199654960018!2m3!1f0!2f0!3f0!3m2!1i1024!2i768!4f13.1!3m3!1m2!1s0x31cc4d0b59
            width="400"
            height="300"
            style="border:0;"allowfullscreen=""
            loading="lazy"
            referrerpolicy="no-referrer-when-downgrade">
        </iframe>
    </div>
</div>
```

Predict the result

```
def predict():

    gambar = file.filename
    print(gambar)

    # Assuming your custom extraction functions
    raw_features = extract.start(gambar)
    raw_baseline_angle = raw_features[0]
    baseline_angle, comment0 = categorize.determine_baseline_angle(raw_baseline_angle)
    print("Baseline Angle: " + comment0)

    raw_top_margin = raw_features[1]
    top_margin, comment1 = categorize.determine_top_margin(raw_top_margin)
    print("Top Margin: " + comment1)

    raw_letter_size = raw_features[2]
    letter_size, comment2 = categorize.determine_letter_size(raw_letter_size)
    print("Letter Size: " + comment2)

    raw_line_spacing = raw_features[3]
    line_spacing, comment3 = categorize.determine_line_spacing(raw_line_spacing)
    print("Line Spacing: " + comment3)

    raw_word_spacing = raw_features[4]
    word_spacing, comment4 = categorize.determine_word_spacing(raw_word_spacing)
    print("Word Spacing: " + comment4)

    raw_pen_pressure = raw_features[5]
    pen_pressure, comment5 = categorize.determine_pen_pressure(raw_pen_pressure)
    print("Pen Pressure: " + comment5)

    raw_slant_angle = raw_features[6]
    slant_angle, comment6 = categorize.determine_slant_angle(raw_slant_angle)
    print("Slant: " + comment6)
```

```
    # Create result dictionary
    result = {
        'Filename': gambar,
        'Baseline Angle': comment0,
        'Top Margin': comment1,
        'Letter Size': comment2,
        'Line Spacing': comment3,
        'Word Spacing': comment4,
        'Pen Pressure': comment5,
        'Slant': comment6,
        'Model 1 Prediction': str(clf1.predict([[baseline_angle, slant_angle]])),
        'Model 2 Prediction': str(clf2.predict([[letter_size, pen_pressure]])),
        'Model 3 Prediction': str(clf3.predict([[letter_size, top_margin]])),
        'Model 4 Prediction': str(clf4.predict([[line_spacing, word_spacing]])),
        'Model 5 Prediction': str(clf5.predict([[slant_angle, top_margin]])),
        'Model 6 Prediction': str(clf6.predict([[letter_size, line_spacing]])),
        'Model 7 Prediction': str(clf7.predict([[letter_size, word_spacing]])),
        'Model 8 Prediction': str(clf8.predict([[line_spacing, word_spacing]])),
    }
```

Analyse the handwriting image

```
.then(data => {
    console.log('Prediction response:', data);
    const predictionsDiv = document.getElementById('predictions');
    predictionsDiv.innerHTML = ''; // Clear previous results
    predictionsDiv.innerHTML += `<br><div><strong>Handwriting Features has been analysed successfully as below!</div>`;
    predictionsDiv.innerHTML += `<div><strong>Baseline Angle:</strong> ${data['Baseline Angle']}</div>`;
    predictionsDiv.innerHTML += `<div><strong>Top Margin:</strong> ${data['Top Margin']}</div>`;
    predictionsDiv.innerHTML += `<div><strong>Letter Size:</strong> ${data['Letter Size']}</div>`;
    predictionsDiv.innerHTML += `<div><strong>Line Spacing:</strong> ${data['Line Spacing']}</div>`;
    predictionsDiv.innerHTML += `<div><strong>Word Spacing:</strong> ${data['Word Spacing']}</div>`;
    predictionsDiv.innerHTML += `<div><strong>Pen Pressure:</strong> ${data['Pen Pressure']}</div>`;
    predictionsDiv.innerHTML += `<div><strong>Slant:</strong> ${data['Slant']}</div>`;
    predictionsDiv.innerHTML += `<br><div><strong>Based on picture ${data['Filename']} above, the person has been diagnosed with: </strong></div>`;
    if (data['Model 1 Prediction'] == "[1.]"){
        predictionsDiv.innerHTML += `<div><strong>${data['Filename']} has the Emotional Stability</strong></div>`;
        predictionsDiv.innerHTML += `<div>Emotional stability refers to a person's ability to remain calm, resilient, and consistent in mood and behavior, even under stress or pre
        invDesc += `\nThis person has Emotional Stability because Baseline Angle: ${data['Baseline Angle']} and Slant: ${data['Slant']}\n`;
        invDesc += `Emotional stability refers to a person's ability to remain calm, resilient, and consistent in mood and behavior, even under stress or pressure. Individuals wit
    }
    if (data['Model 2 Prediction']== "[1.]"){
        predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has the Mental Energy or Will Power:</strong></div>`;
        predictionsDiv.innerHTML += `<div>Mental energy or Will Power is the capacity to focus, resist distractions, and persist in tasks despite challenges. It encompasses the me
        invDesc += `\nThis person has Mental Energy because Letter Size: ${data['Letter Size']} and Pen Pressure: ${data['Pen Pressure']}\n`;
        invDesc += `Mental energy or Will Power is the capacity to focus, resist distractions, and persist in tasks despite challenges. It encompasses the mental stamina required
    }
    if (data['Model 3 Prediction']== "[1.]"){
        predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has the Personal Harmony and Flexibility</strong></div>`;
        predictionsDiv.innerHTML += `<div>Personal harmony is the state of inner balance and peace, where one's thoughts, emotions, and actions are in alignment, fostering a sense
        invDesc += `\nThis person has Personal Harmony and Flexibility because Line Spacing: ${data['Line Spacing']} and Word Spacing: ${data['Word Spacing']}\n`;
        invDesc += `Personal harmony is the state of inner balance and peace, where one's thoughts, emotions, and actions are in alignment, fostering a sense of well-being and con
    }
```

```
if (data['Model 4 Prediction']== "[1.]"){
    predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has Modesty attitude</strong></div>`;
    predictionsDiv.innerHTML += `<div>Modesty is the quality of having a humble and unassuming view of one's own abilities, achievements, or importance. It involves recognizi
    invDesc += `\nThis person has Modesty because Top Margin: ${data['Top Margin']} and Letter Size: ${data['Letter Size']}\n`;
    invDesc += `Modesty is the quality of having a humble and unassuming view of one's own abilities, achievements, or importance. It involves recognizing one's strengths and
}
if (data['Model 5 Prediction']== "[1.]"){
    predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has Lack of Dicipline:</strong></div>`;
    predictionsDiv.innerHTML += `<div>Lack of discipline is the inability to consistently control one's actions, impulses, and desires to achieve long-term goals. It manifest
    invDesc += `\nThis person has Lack of Dicipline because Slant Angle: ${data['Slant']} and Top Margin: ${data['Top Margin']}\n`;
    invDesc += `Lack of discipline is the inability to consistently control one's actions, impulses, and desires to achieve long-term goals. It manifests as procrastination,
}
if (data['Model 6 Prediction']== "[1.]"){
    predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has Poor Concentration:</strong></div>`;
    predictionsDiv.innerHTML += `<div>Poor concentration is the difficulty in maintaining attention and focus on a task or activity for a sustained period. It often leads to
    invDesc += `\nThis person has Poor Concentration because Letter Size: ${data['Letter Size']} and Line Spacing: ${data['Line Spacing']}\n`;
    invDesc += `Poor concentration is the difficulty in maintaining attention and focus on a task or activity for a sustained period. It often leads to frequent distractions,
}
if (data['Model 7 Prediction']== "[1.]"){
    predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has Non Communicativeness personality:</strong></div>`;
    predictionsDiv.innerHTML += `<div>Non-communicativeness is the tendency to refrain from sharing thoughts, feelings, or information with others. It manifests as limited ve
    invDesc += `\nThis person has Non Communicativenes because Letter Size: ${data['Letter Size']} and Word Spacing: ${data['Word Spacing']}\n`;
    invDesc += `Non-communicativeness is the tendency to refrain from sharing thoughts, feelings, or information with others. It manifests as limited verbal interaction, relu
}
```

```
if (data['Model 8 Prediction']== "[1.]"){
    predictionsDiv.innerHTML += `<br><div><strong>${data['Filename']} has the Social Isolation attitude:</strong></div>`;
    predictionsDiv.innerHTML += `<div>Social isolation refers to the state of being separated from social interactions or relationships with others. It involves limited partic
    invDesc += `\nThis person has Social Isolation because Line Spacing: ${data['Line Spacing']} and Word Spacing: ${data['Word Spacing']}\n`;
    invDesc += `Social isolation refers to the state of being separated from social interactions or relationships with others. It involves limited participation in social acti
}
```

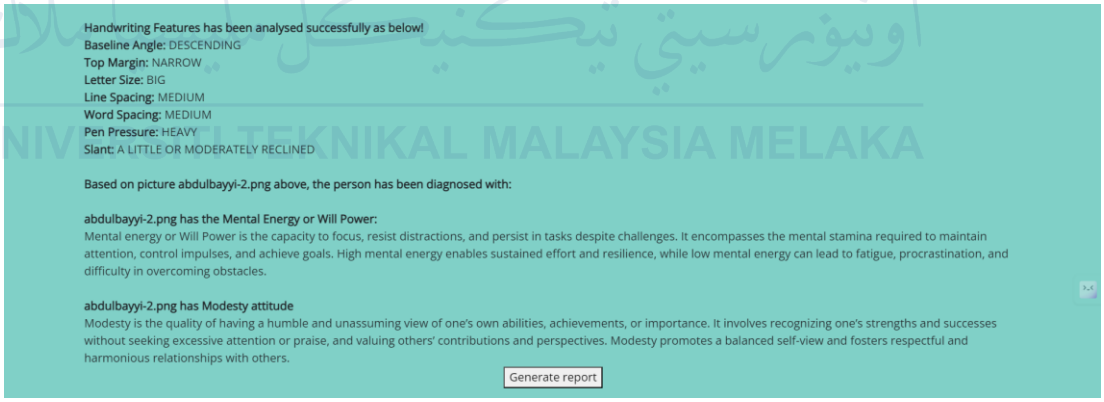
APPENDIX B: USER MANUAL

Interface: Analysis

Action: Click ‘Choose File’ to upload a handwriting image

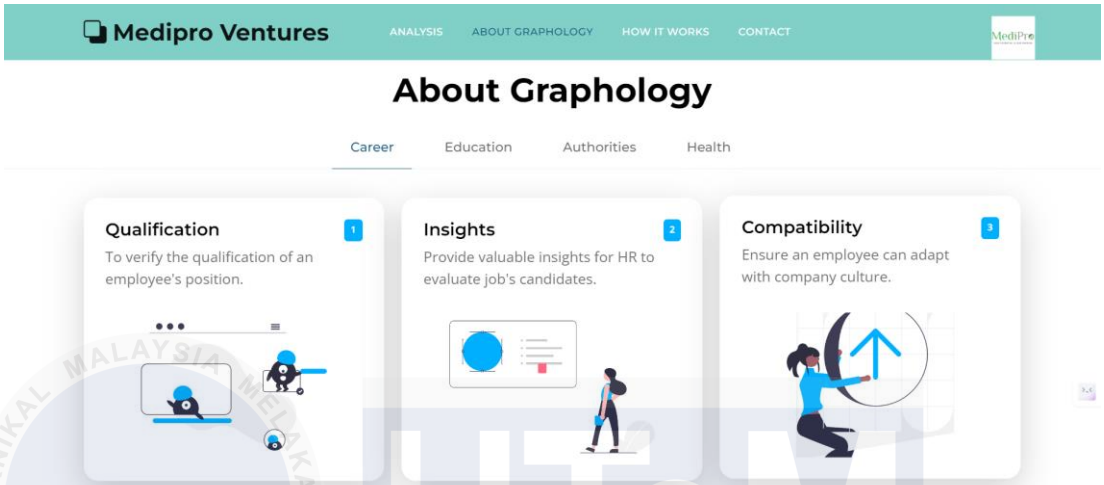
Action: Click ‘Predict’ to get the analysis result after uploading image

Action: Click ‘Generate report’ to get the analysis report after obtaining the analysis



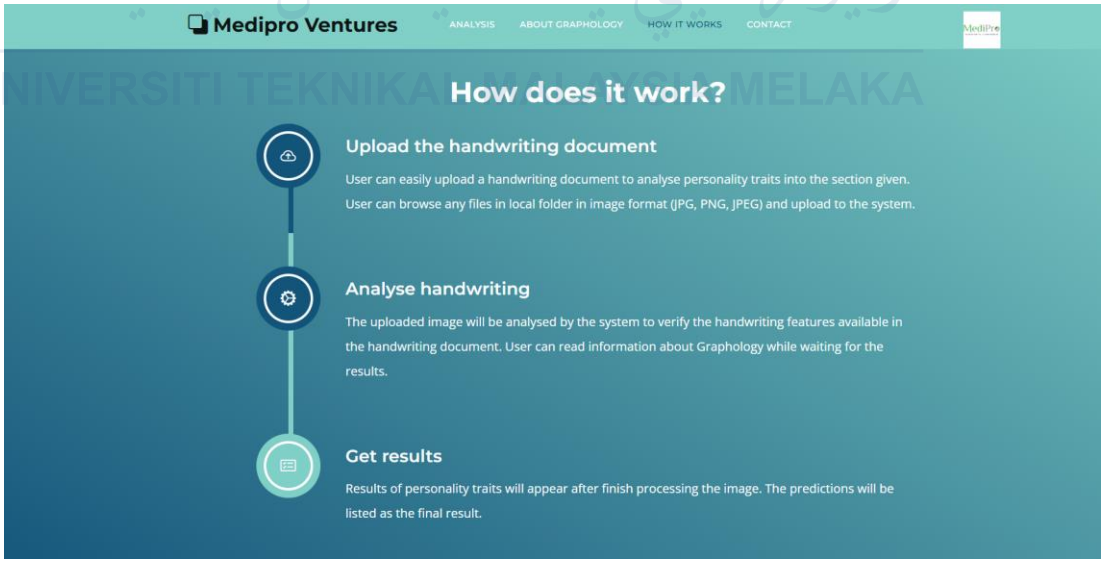
Interface: About Graphology

Action: Click any button on the top bar to view the information on graphology related to career, education, authorities and health.



Interface: How it works

Action: Scroll down to see how the AI-Based Handwriting Analysis System works.

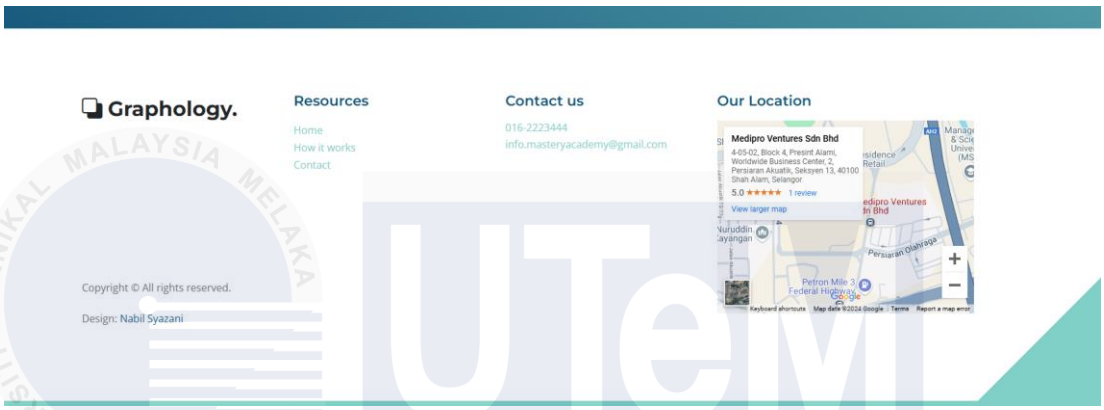


Interface: Footer section

Action: Choose any button under ‘Resources’ to navigate back to the section

Action: Choose a phone number or email under ‘Contact Us’ to directly link to the contact number or compose an email.

Action: Explore the location in ‘Our Location’ section. Directly link to Google Maps application and have a direction.



APPENDIX C: DOMAIN EXPERT CREDIT

About Dr. Azura Hashim

+6016-222-3444
hello@graphology.com.my

Azura Hashim

DR AZURA HASHIM adalah pengasas bersama Mastery Academy, sebuah syarikat yang memfokuskan latihan dan pembangunan yang bermatlamat membangunkan kemahiran dan potensi masyarakat sekeliling. Mastery Academy juga memberi tumpuan kepada pembangunan usahawan untuk meningkatkan perniagaan dengan kaedah yang berkesan dan terlibat di dalam bidang penerbitan buku.

Dr Azura menerima pendidikan MBA dan PhD dalam Pemasaran Antarabangsa. Merupakan Certified Neuro-Linguistic Programming (NLP) Coach di bawah naungan National Federation of Neuro-Linguistic Programming (NFNLP, USA). Beliau juga mempunyai kepakaran sebagai Master of Handwriting Analysis yang diiktiraf oleh KAROHS International School of Handwriting Analysis, Amerika Syarikat.

Beliau mempunyai kelayakan sebagai trainer HRDF, Certified Practitioner Mindfulness Love Therapy, Certified Advance Neo-Cognitive and Behaviour, Practitioner Art Drawing-House Tree Person, Cognitive Fitness dan Positive Psychology dari Harvard Medical School.

Bidang kepakaran beliau adalah menerokai minda separa sedar melalui tulisan dan lukisan, pembangunan keusahawanan, pembangunan diri, komunikasi & kepimpinan, Neuro-Linguistic Programming & pengurusan emosi dan terapi kehidupan dengan Asmaul Husna.

Berpegang kepada life-long learning dan semangat yang tinggi, beliau bercita-cita membantu individu sekeliling mengubah kehidupan secara mental, emosi, fizikal dan rohani dengan lebih berkesan.

Dr Azura mempunyai pengalaman bekerja dalam industri lebih dari 15 tahun. Beliau berpengalaman dalam bidang telekomunikasi, pendidikan dan industri kewangan. Merupakan pengarah di Medipro Ventures Sdn Bhd, pengasas bersama Mastery Academy, berpengalaman sebagai Director Consultant, BNI (Business Networking), pensyarah di Universiti Malaya, pengurus di Jabatan Hartanah di UMobile Sdn Bhd dan Head of Site Acquisition & Property di Digi Telecommunication.

Antara subjek yang pernah diajar oleh beliau semasa bergelar pensyarah di Universiti Malaya adalah e-pemasaran, sumber manusia dan gelagat pengguna.
Secara aktifnya beliau telah membuat banyak perkongsian bersama pelbagai organisasi badan

kerajaan dan swasta sejak 8 tahun lepas, termasuklah di **Majlis Amanah Rakyat, KWSP, Socso, Lembaga Tabung Haji, Bernama, KPDNKK, PTPK** dan banyak lagi. Program seminar Dr Azura telah disambut baik dan mendapat maklum balas yang positif daripada kumpulan peserta pelbagai terdiri daripada usahawan, majikan, golongan pekerja, dan umum.

Seringkali dijemput di saluran media massa seperti **Malaysia Hari Ini (MHI) TV3, TV AlHijrah, IKIM.fm, BERNAMA, majalah In Trend, akhbar The Star, Sinar Harian, Utusan Malaysia dan Harian Metro**. Selain itu, sering dijemput untuk berkongsi buah fikiran di majalah dan akhbar selain aktif menulis dan telah menulis 5 buah buku yang best-selling.

Beliau mempunyai impian yang tinggi untuk membantu orang sekeliling meningkatkan kecekapan, kemahiran dan potensi diri mereka. Percaya dengan kepakaran yang dimiliki, di tambah pula pengalaman sewaktu dalam industri. In Shaa Allah dapat menyumbang kepada kumpulan di luar sana untuk lebih berjaya dalam kehidupan, organisasi dan negara secara keseluruhan.

Beliau boleh dihubungi melalui:

Facebook : Azura Hashim
Facebook Page : Dr Azura Hashim
Instagram : drazurahashim
YouTube : Dr Azura Hashim
Website : www.drazurahashim.com
Telefon : 016-222-3444


WOW!
Korana dirimu istimewa...
Telekung solat Adra
MS 5
Hello Hong Kong
MS 10
Bajet kecantikan
MS 2-4
Rawat diri: Guna info internet berbahaya?
MS 8
Azura pakar tulisan tangan
MS 6
BISNES
Dapatkan sisipan BISNES esok!


WOW! Personaliti Minggu Ini
AHAD | 4 SEPTEMBER 2016 | www.sinarharian.com.my/rencana
Berkongsi minat & kepakaran
Niat Azura membantu individu ke arah kehidupan positif

PENAMPILAN AZURA HASHIM DI MEDIA