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Personality Prediction Model: An Enhanced Machine Learning Approach

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Abstract

In today's digital era, social media platforms like Instagram have become deeply embedded in daily life, generating billions of content items each day. This vast stream of publicly accessible data presents a unique opportunity for researchers to gain insights into human behaviour and personality. However, leveraging such unstructured and highly variable data for psychological analysis introduces significant challenges, including data sparsity, noise, and ethical considerations around privacy. This study addresses these challenges by exploring the potential of machine learning to infer personality traits from Instagram content. Motivated by the growing demand for scalable, non-intrusive methods of psychological assessment, we developed a personality prediction system combining convolutional neural networks (CNNs) and random forest (RF) algorithms. Our model is grounded in the Big Five Personality framework, which includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. Using data collected with informed consent from 941 participants, we extracted visual features from their Instagram images using two pretrained CNNs, which were then used to train five RF models, each targeting a specific trait. The proposed system achieved an average mean absolute error of 0.1867 across all traits. Compared to the PAN-2015 benchmark, our method demonstrated competitive performance. These results highlight that using social media data for personality prediction offers potential applications in personalized content delivery, mental health monitoring, and human–computer interactions.

Keywords: personality prediction; machine learning; big five personality; Extraversion; Agreeableness; Conscientiousness; Neuroticism; Openness

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Received: 26 May 2025
Revised: 16 June 2025
Accepted: 18 June 2025
Published: 24 June 2025

Citation: Ashawa, M.; Bryan, J.D.; Owoh, N. Personality Prediction Model: An Enhanced Machine Learning Approach. *Electronics* **2025**, *14*, 2558. https://doi.org/10.3390/electronics14132558

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1. Introduction

With the advent of the internet, the amount of data being created and collected is truly immense. With about 2.5 quintillion bytes of data being generated each day [1] and with a sizable portion of that data coming from social media sites, it has become a goldmine for researchers. With billions of active users on social media sites [2], there is an abundance of data that can be used to find patterns and correlations between personality and digital footprints. This can be achieved by using machine learning to analyse the data and create correlations between user personality and their social media data [3]. Identifying personality traits through digital patterns enables applications in counselling, recruitment, and finance to personalize services, improve decision-making, and enhance user experiences [4].

However, despite the promising potential of personality prediction from social media data, several challenges continue to hinder meaningful progress and widespread adoption in applied settings. First is the absence of a unified, scalable methodology for accurately linking diverse forms of social media content such as text, images, metadata, and user interactions to establish and validate psychological personality models. While there are existing models that try to solve these challenges, their approaches vary significantly in terms of data sources and feature engineering strategies. This often leads to limited generalizability across different user populations and platforms. This lack of standardization makes it difficult to compare findings across studies or deploy these systems in real-world scenarios with confidence, especially when such systems are modelled for social media platforms such as Instagram.

Second, there are ethical and legal concerns surrounding the use of user-generated content for psychological inference. Many users are unaware of the extent to which their online activity can be analysed to derive personal attributes, including mental health status and personality traits. This asymmetry of awareness introduces serious concerns about informed consent, autonomy, and the potential misuse of the generated data. Addressing these challenges requires the development of a framework that incorporates ethical safeguards to ensure data anonymization and to provide clear communication to users about how their data will be used. Only by synchronizing both technical inconsistencies and ethical vulnerabilities can an effective and scalable personality prediction model for real-world deployment be achieved.

Instagram is a social media platform owned by Meta [5]. Instagram enables users to upload and share images and videos with their followers, who can view, like, and comment on the posts. As the fourth most popular social media platform globally, it boasts over 1.5 billion active users [6]. The platform generates a vast amount of data daily. This presents a significant challenge in terms of efficient data collection. This process is complicated by ethical and technical considerations, particularly since the data is user-generated and may contain personally identifiable information. Application Programming Interfaces (APIs) offer a method for gathering data in an efficient and timely manner, provided that user consent has been obtained. To analyse and predict future personality traits, participants' personalities should be assessed using established frameworks such as the Big Five Inventory (BFI), the Big Five Inventory-10 (BFI-10), the International Personality Item Pool (IPIP), or the Ten Item Personality Measure (TIPI) [7].

While the highlighted personality models are considered effective for Conscientiousness with a proven dominance effect, they are limited to some extent [8]. For instance, with the dynamic nature of social media platforms like Instagram, individuals are frequently exposed to curated content, social comparisons, and changing social norms. This environment can influence behaviour and self-presentation, potentially leading to shifts in personality traits over time, particularly traits like Conscientiousness. As a result, models that assume trait stability may become less accurate in predicting behaviour.

To address the aforementioned issues, this paper proposes two distinct network personality models. First, we propose a CNN model to analyse patterns within Instagram users' photos. Second, we propose an RF algorithm that is trained on both Instagram users' metadata and the processed outputs from the CNN to predict users' personalities. Volunteers using Instagram were recruited to make a dataset for this research. The volunteer's personality test was recorded on a spreadsheet to allow the data to be easily passed into the program in an organised way for easy analysis. The data was extracted from the spreadsheet, and the personalities of the volunteers were calculated.

To analyse the volunteers' data, it was first collected by downloading it from Instagram using their public APIs. Images contained important data for this research, so pretrained

CNNs were used to extract relevant personality-related features from them. A Random Forest algorithm was then created, and all data points, including processed data from CNN and other recorded inputs, were used to make a final prediction of the user's personality. Users uploaded their own Instagram data into the personality prediction system, which was then analysed, and the results were displayed. The research question that guided the development of this model is, "Can a personality prediction system created by analyzing data from Instagram accounts with a focus on feature extraction from images be considered accurate when evaluating different regression scoring metrics?" This research made the following contributions:

1. We propose a novel personality prediction framework that estimates the Big Five personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness) from Instagram image data by leveraging two pretrained convolutional neural networks (CNNs) for robust feature extraction. The model explicitly addresses the challenge of generalizability across diverse populations to mitigate social desirability bias.
2. We present a hybrid methodology for personality inference that integrates CNNs with ensemble learning through Random Forest regressors. Comprehensive hyperparameter optimization is employed to maximize predictive performance.
3. We conduct a critical review of machine learning approaches to personality prediction to highlight their strengths and limitations to contextualize the proposed model.

The structure of this paper is as follows: Section 2 reviews related literature on personality prediction methodologies, including reliability assessments and a comparative analysis of existing approaches. Section 3 outlines the comprehensive methodology for model development, covering stages from data acquisition and feature extraction to prediction modelling. Section 4 presents the experimental findings, discusses evaluation metrics, and benchmarks the proposed model against established personality prediction frameworks. Finally, Section 5 concludes the study by highlighting the implications of the results and proposing directions for future research in personality detection.

2. Related Works

To effectively contextualize the research on the Personality Prediction Model from Instagram Users Using Machine Learning, it is essential to examine the foundation laid by prior studies in the domain of computational personality assessment. A study was conducted employing Generalizability Theory to evaluate the reliability of the Big Five Inventory (BFI) [9]. Reliability was assessed using Cronbach's Alpha, with a score greater than 0.7 deemed acceptable, and through Test-Retest reliability, where a coefficient above 0.75 is considered acceptable. The study found that the Big Five Inventory was reliable based on both its internal consistency (Cronbach's Alpha) and its stability over time (Test-Retest reliability). The proposed model in this paper relies on reliable personality assessments like the BFI to evaluate and compare its predictions. If the machine learning model accurately predicts personality traits, it should ideally correlate with these reliable BFI measures. A foundational element of our model is its reliance on the Big Five Inventory (BFI), which is a widely used and validated personality assessment tool. By aligning our model's predicted traits with the BFI, we ensure comparability with established personality metrics. However, it is important to acknowledge the limitations of the Five-Factor Model (FFM) on which the BFI is based.

Research has shown that the FFM may not generalize across all cultural contexts, particularly in non-literate or rural societies. In [10], the study indicates that the Five-Factor Model (FFM) may not be universally applicable across all societies. The authors argue that the FFM serves as a valid measure of personality, primarily in literate and urbanized

contexts. This suggests that machine learning models based on FFM might be less effective or less accurate in rural or non-literate societies, just as the FFM might not universally apply across all cultures. As societies become more literate and urbanized, they adopt more complex systems of identity, social roles, and psychological expressions that FFM can measure [11]. Non-literate or rural societies, which are more likely to rely on oral traditions, less formalized structures of communication, and community-based relationships, may not exhibit personality traits in ways that align with FFM. The absence of certain markers, such as the use of language or social media interactions as proxies for openness or extraversion in such societies, could skew the FFM model's effectiveness [12]. This informs our decision to focus on Instagram users who predominantly represent urban and literate populations where the FFM is more applicable.

The application of social media data for personality prediction has been successfully demonstrated in previous studies, particularly those using Facebook data. In [13], the authors collected Facebook user profiles and status updates to develop a system aimed at predicting individual personality traits based on social media activity. The study employed the Big Five Personality traits (Extraversion, Neuroticism, Agreeableness, Conscientiousness, and Openness to Experience) as the theoretical framework for personality classification. Each dimension is treated as a continuous latent construct, enabling nuanced trait quantification at the individual level. By leveraging this framework, the study benefits from a robust psychological taxonomy that has demonstrated high construct validity and cross-cultural applicability. The integration of the Big Five facilitates alignment with standardized psychometric instruments (e.g., BFI, NEO-PI-R) that allow for more interpretable and comparable modeling outcomes across computational personality research.

Distinct from previous research that predominantly utilized traditional machine learning approaches, this work investigates the applicability of deep learning techniques, achieving a classification accuracy of 74.17%. The model's use of real-world Facebook profiles and status updates enhances ecological validity, providing insights into naturally occurring digital behaviour [14]. However, a significant limitation lies in its reliance on the Big Five Personality Model, which may not generalize well across diverse cultural contexts. A data-driven and multimodal deep learning trait model like the CNNs will adopt cultural generalization using regional fine-tuning for high validity and domain adaptation through image, text, and social interaction patterns. While such models relied on textual data and traditional ML methods, our approach advances this line of work by applying deep learning techniques to Instagram, which is a platform that is more visually oriented. Our approach toward image-rich data not only improves ecological validity, as demonstrated in [14], but also aligns with current trends in affective computing and vision-based personality prediction.

Recent advancements in affective computing and sentiment analysis have increasingly focused on the automatic identification of personality traits from textual data. Earlier approaches primarily relied on handcrafted feature engineering techniques, such as linguistic style analysis and psycholinguistic resource utilization, to identify correlations with personality dimensions. However, the field has seen a paradigm shift with the advent of transfer learning in natural language processing (NLP) [15], particularly through the use of pre-trained language models that allow for both feature extraction and fine-tuning. The proposed model builds on recent progress in NLP by incorporating transfer learning through pre-trained language models. This approach allows for more understanding of feature extraction and improved generalization.

A study [16] proposed a deep learning-based framework that integrates both data-level and classifier-level fusion to enhance personality classification. Using NLP models with increase in classification accuracy by approximately 1.25%. However, important personality

biases, such as opinions and mood, were not captured by the model. To address such limitations, our model integrates both visual and textual inputs from Instagram to capture a broader emotional spectrum.

Multimodal approaches have shown considerable promise in personality prediction. In [17], a deep learning framework for multimodal personality prediction was proposed. The model integrated visual, auditory, and textual information. Facial signs and contextual scene elements were extracted via Multi-task Cascaded Convolutional Networks (MTCNN) and ResNet. Although the approach in [17] was constrained by limited image input diversity, it demonstrated the effectiveness of integrating multiple data types. While the model explored both feature concatenation and attention-based mechanisms to enhance multimodal integration, a limited set of image inputs was used. Our model extends this idea by leveraging Instagram's diverse visual content and combining it with textual indications such as captions and hashtags to improve prediction accuracy and cultural generalizability.

Similarly, the research in [18] provided a comprehensive review of the current landscape in automated personality trait prediction, with a strong emphasis on multimodal deep learning-based approaches. It systematically analyses and synthesizes state-of-the-art machine learning models. The findings of this research highlight the growing potential of machine learning-driven systems in understanding human behaviour, which significantly enhances applications in different fields such as recruitment, marketing, education, and human–computer interaction. The reviewed study in [18] highlights the effectiveness of a multimodal deep learning model that integrates multiple data types such as images and audio. Our proposed model adopts the same strategy by leveraging Instagram's multiple data types with more holistic modelling of the human behavioural approach.

In summary, the reviewed studies narrowed the contextual understanding of personality traits and limited the integration of interdisciplinary insights, which is necessary for holistic personality modelling [19]. Building upon these findings, our study uses Instagram's image-rich environment as a primary data source for data collection and feature extraction. This aligns with recent trends in affective computing, where vision-based models complement traditional textual analyses to improve prediction. As summarized in Table 1, these existing personality prediction models have limitations.

Table 1. Comparison of Related Works Used in Personality Prediction.

Related Works	Research	Method Used	Results	Strengths	Limitations
[9]	Reliability of BFI in personality assessment	Generalizability Theory, Cronbach's Alpha, Test-Retest	BFI found to be reliable ($\alpha > 0.7$; test-retest > 0.75)	Strong empirical validation of BFI	Focused only on psychometric reliability
[10–12]	Cultural generalizability of FFM	Comparative analysis across societies	FFM effective in urban, literate societies	Highlights cultural limitations of FFM	Limited in scope to cultural analysis, not ML modeling
[13,14]	Predicting personality from Facebook data	Deep learning using Facebook statuses with BFI labels	74.17% classification accuracy	Use of real-world social media enhances ecological validity	Relies heavily on FFM; potential cultural/linguistic bias

Table 1. *Cont.*

Related Works	Research	Method Used	Results	Strengths	Limitations
[15,16]	Text-based personality prediction via NLP	Pretrained language models, feature fusion	Accuracy improved by ~1.25% using deep learning fusion	Modern NLP techniques and improved prediction performance	Misses subjective elements like mood/opinion in text
[17]	Multimodal deep learning personality model	Visual, auditory, and text features via CNN (ResNet, MTCNN)	Effective multimodal fusion; enhanced prediction	Integration of multiple data types enhances robustness	Limited visual dataset constrains generalizability
[18]	Survey of multimodal personality prediction	Systematic review of ML approaches	Identified potential of AI in HCI, marketing, recruitment	Comprehensive overview of computational methods	Ignores psychological frameworks; narrow perspective

3. Materials and Methods

3.1. Data Collection

Data acquisition began with the design of a structured questionnaire based on the Big Five Personality Traits model, comprising 44 items aimed at quantitatively assessing personality dimensions. An informed consent section was included at the beginning of the questionnaire to ensure ethical compliance and voluntary participation. The survey was created using Microsoft Forms and disseminated through professional and social platforms, including LinkedIn and Instagram, over an eight-week period. A total of 941 participants provided consent and completed the questionnaire. Respondents were requested to confirm their submissions to enable the accurate linkage of their Instagram profiles with the collected data, thereby supporting subsequent multimodal analysis.

Responses were exported via the native functionality of Microsoft Forms to ensure data integrity and ease of organization. The dataset was processed to prepare it for analysis, including steps for response validation, scoring based on the Big Five Inventory, and preparing data for model input. Due to the inclusion of personally identifiable information, the dataset is not publicly available. However, all scripts used in data preprocessing and model development are available in the accompanying open-source repository: https://github.com/JoshuaBryan02/Personality-Prediction-System (accessed on 29 May 2025). Figure 1 presents a detailed flow diagram illustrating the systematic development process of the proposed personality prediction system.

The complete computational procedure for trait scoring is formalized in Algorithm 1. A schematic overview of the preprocessing workflow and model development pipeline is illustrated in Figure 1, highlighting the modular and systematic nature of the approach. As shown in Figure 2, a systematic sequence of preprocessing and implementation steps was employed to ensure the effective development of the prediction model.

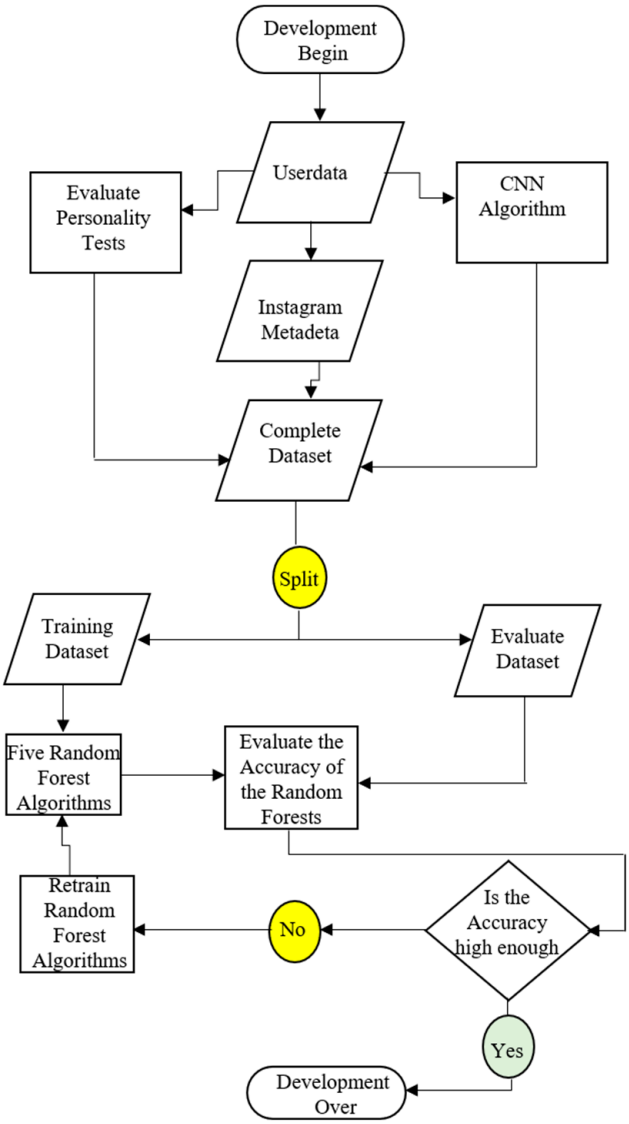


Figure 1. Flowchart of the Proposed Model.

Algorithm 1 *Personality Scores Calculation*	
Input:	*Personality_Scores_Dataset*
Output:	*Lists of calculated scores for each of the five personality traits*
1.	*dataset Load_Personality_Test ()*
2.	*convert loaded_data into list of values y()*
3.	*set counters x* $(x = 0,\ xx = 0)$
4.	*fix variable* $z = 44$
6.	***with*** $y\ \forall_i \quad x_i = 0$
7.	*compute_scores_and_update_initialised_lists*
8.	*return display_results_for_lists_containing_scores y (extraversion, agreeableness, conscientiousness, neuroticism, openness)*

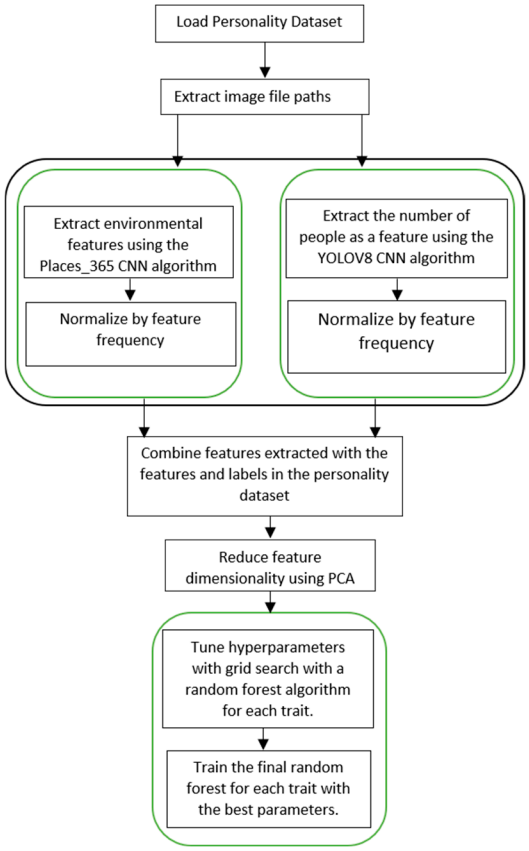


Figure 2. The Proposed Personality Prediction Model.

3.2. Data Extraction

A Python-based data processing pipeline was developed to facilitate the preprocessing and analysis of raw survey data collected via Microsoft Forms. The core script, titled CSV-splitting.py [link], was designed to automate the transformation of raw inputs into structured personality trait scores based on the Big Five Inventory (BFI) framework [20]. The extraction begins with the definition of file path variables to locate the original dataset and check for prior executions. Upon initialization, the script prompts the user to confirm that they can proceed if previous processing results exist.

The raw dataset originally stored in Microsoft Excel (.xlsx) format was converted into a standardized comma-separated values (.csv) format using the pandas library in Python version 3.13.5. This conversion ensured compatibility with downstream data processing routines to facilitate efficient parsing. To clearly separate the data, the converted dataset extracts two distinct files, one containing participant consent information and the other comprising responses to the BFI questionnaire for personality test. The later file reads the processed personality assessment data and computes individual traits for personality score computation by initializing data structures for each of the five BFI dimensions based on validated scoring schemes. Reverse scoring and normalization techniques are applied internally where required to ensure data consistency and comparability.

To measure personality traits in alignment with the Big Five Inventory (BFI), a systematic data processing was created to centre on trait-wise aggregation and normalization [21] of questionnaire responses. The framework employs a nested iteration structure wherein each participant's response vector is individually processed to ensure accurate mapping of item-level responses to the five BFI dimensions.

Each response was scored in accordance with the Big Five Inventory (BFI) guidelines [22], with individual data points allocated to one of the five personality traits based

on the corresponding questionnaire item. During each iteration of the outer loop, the counter advanced to the next index, effectively separating responses by the participant. To accommodate items requiring reverse scoring, a custom function was implemented. This function performs a transformation such that a score of 5 is converted to 1, 4 to 2. This aligns with the BFI's reversed scoring mechanism [23]. The function is invoked conditionally based on the reverse-coded nature of specific questions, as presented in Algorithm 2.

Algorithm 2 *Reverse Code*

Input:	*Number_to_reverse [1 to 5]*
Output:	*Reversed_score*
1.	*define close interval ($x \in \mathbb{Z}$ such that $1 \leq x \leq 5$)*
2.	*check and reverse score:*
3.	***if*** *$1 \leq$ number_to_reverse ≤ 5:*
4.	***endif***
5.	*output = 6 (number_to_reverse)*

To ensure consistency and comparability across participants, the raw personality trait scores were normalized using min-max scaling. This transformation mapped the original scores onto a [0, 1] interval, which were then scaled to a [0, 100] range to enhance interpretability as percentage-based trait intensities.

The normalization bounds were determined based on the theoretical minimum and maximum values for each trait, calculated from the total number of associated questionnaire items and the Likert scale range (1–5). This approach preserves the relative differences in trait expression while allowing for standardized comparisons across individuals. The normalized scores for the five traits were structured into a unified dataset to support downstream tasks such as model training, evaluation, and visual analysis. This design choice facilitates streamlined data integration and aligns with best practices in personality prediction studies employing a supervised learning approach.

3.3. Instagram API Instaloader

This subsection outlines data initialization and user management. To facilitate systematic data collection, a Python-based utility was developed using the Instaloader library. Instaloader is chosen for its robustness in scraping publicly accessible Instagram content while supporting session-based authentication. The system ingests participant information (usernames and dates of birth) from a consent-managed file. This file is derived from the prior processing step to ensure that only users who have formally agreed to participate are included in the dataset. For personality inference on new users, our framework allows manual input of credentials that are dynamically appended to the processing pipeline for the scalability of the system for both experimental and real-time prediction contexts.

Data retrieval when is automated where an instance of the Instaloader class is initialized with parameters configured to collect image posts and video thumbnails exclusively. This was to focus the model's input on visual content, which is central to Instagram-based self-presentation. To ensure relevance to adult personality development, each post's timestamp is compared to the user's 18th birthday, and only posts made on or after this age threshold are retained. This design choice is grounded in psychological literature suggesting that stable personality traits emerge during late adolescence. The content for each eligible post is then downloaded and stored in a user-specific directory named after the Instagram handle to preserve data organization and traceability.

To enable authenticated scraping, which is necessary for retrieving certain user-specific content, a secure session cookie is imported into the Instaloader environment to prompt

the user for their Instagram handle, from which a valid session is retrieved and imported. This session management approach ensures compliance with Instagram's access controls while minimizing the risk of request denial due to unauthenticated access.

To mitigate the risk of surpassing Instagram's API rate limits, a randomized delay is introduced between post-retrieval iterations. This delay ranges from 20 to 50 s to generate a pseudo-random number generator implemented through a sleep function. The program prompts the user to input their Instagram username, which is used by a pre-initialized instance of the Instaloader class to retrieve the corresponding session cookie. This session is then imported into the program. This process allows the instance to operate within an authenticated environment. A loop is then implemented to iterate through a predefined list of usernames. During each iteration, a temporary list is instantiated to store the data associated with the current user.

The username is extracted and sanitized by removing any leading '@' characters which were occasionally appended by volunteers when submitting their Instagram identifiers. In each iteration of the loop, the birthdate corresponding to the volunteer is extracted and converted into a Python datetime object using the strptime function. To compute the date on which the volunteer attained the age of eighteen, a time delta object equivalent to 18 years is added to the original birthdate. When initiated, the volunteer's Instagram profile is accessed by invoking the Profile.from_username method, which requires the Instagram username. This uses a pre-configured Instaloader instance to authenticate the session and enforce download constraints. Once the profile object is instantiated, essential account metadata such as username, the total number of media posts, follower count, and number of followers is extracted. These data are appended as a new entry to an output CSV file named Instagram_data.csv. A get_posts method is created to retrieve metadata for all posts associated with the profile, including download paths. Prior to initiating the download process, the script verifies the existence of a directory designated for the current user's posts to avoid redundant downloads. Details of this flow are summarized in algorithm 3.

Algorithm 3 *Automated Extraction of Instagram User Data*

Input:	*Instagram_user_profile_object*
Output:	*Username_ Identifier_used_with_downloader_posts*
1.	*get_posts(from_the_user_profile)*
2.	*check if a folder with the name_ username exists:*
3.	***if*** *it does not exist,*
4.	*iterate through the_user's_posts using*
5.	***dropwhile*** *skip posts created* ***before*** *the user's_eighteenth_birthdate*
6.	***takewhile*** *process posts created* ***after*** *the eighteenth_birthday*
7.	*create folder_path by joining output_folder and username.*
8.	***for each*** *qualifying post:*
9.	*download the post into the folder named after the_user*
10.	*randomise delay* $\delta \sim U(20, 50)$
11.	***if*** *counts >150:*
12.	***endif***
13.	***end for***
14.	*return display_results (file_paths, username, dates_of_birth, posts)*

3.4. Model Description

First, the Places365 Convolutional Neural Network (CNN) [24] was employed to extract scene-level contextual features from the Instagram attributes. This model, pretrained on a large-scale scene recognition dataset, was chosen due to its proven ability to capture

high-level semantic information that reflects environmental and lifestyle indicators in personality inference. In parallel, YOLOv8 [25,26] real-time object detection architecture was used to estimate the number of individuals present in each image. This information serves as a proxy for social behaviour and extraversion-related traits to align with the underlying psychological theory linking social presence and personality dimensions.

To streamline the data processing, a structured metadata table was created containing paths to all collected Instagram images. This was compiled by iterating through user-specific directories and aggregating image file paths into a unified dataset. Redundant prefixes in usernames (e.g., "@") were removed during preprocessing to ensure standardized directory handling. The collected paths were then written as new rows into the Image_Paths.csv file, as illustrated in Algorithm 4. Following this, the image paths were loaded from the Image_Paths.csv file and converted into a Python list for further processing. The file labels_sunattribute.txt contains the class labels required by the model which reads line by line with each line appended to a list.

Algorithm 4 *Data Preprocessing*

Input:	*Username_list*
Output:	*Store_image _paths*
1.	***if*** *Image_paths file exists:*
2.	*dele the file*
3.	***else****,*
4.	*open the Image_paths*
5.	***for each*** *username in username_list:*
6.	***if*** *username starts '@', remove '@' from the beginning*
7.	*create folder_path by joining output_folder and username.*
8.	***for each*** *file in the directory folder_path:*
9.	*create img_path by joining folder_path and file*
10.	*append img_path to user_paths*
11.	*return user_paths as Image_paths*

To ensure consistency in label representation and facilitate reproducibility, a conditional routine was implemented to manage the label encoding process. The model first verifies the presence of a pre-fitted label encoder (label_encoder_CNN1.pkl). If the serialized encoder file is absent, a new LabelEncoder instance is initialized and fitted on the available label set, after which it is serialized and stored using Python's pickle module. If the file is present, the encoder is directly deserialized and loaded to ensure reuse across training cycles and prevent redundant computation. The CNN2.py module initiates the feature extraction workflow. It defines a target directory for storing the extracted image features in a structured format. During runtime, an empty list is instantiated to accumulate the features output by the convolutional neural network for each image processed. This approach systematically retrieves image file paths and feeds them into the CNN for representation learning. This checkpoint-driven approach not only optimizes runtime efficiency by avoiding redundant training or encoding processes but also reinforces reproducibility and traceability, both of which are critical in data-driven personality prediction systems.

3.5. Normalization

A nested iterative process was employed to extract frequency-based features from image-level metadata. The outer loop aggregated the occurrence frequency of each individual across all Instagram posts. To ensure comparability across samples, frequencies were normalized by the total number of images per volunteer. A further normalization step

scaled the values to the [0, 1] interval. To mitigate the risk of division-by-zero errors and enhance numerical stability, a small constant offset was added during this transformation.

During the training process, the parameters used for min–max normalization (i.e., the maximum and minimum values) were stored using the pickle module. This approach ensures that the same normalization scale can be applied consistently during model inference to preserve feature alignment across model deployments. The resulting feature set was organized into a structured pandas DataFrame.

To predict personality traits, the personality classification process was implemented using Python, with a Random Forest model serving as the baseline algorithm due to its robustness against overfitting and interpretability. The process integrates multiple feature sources: environmental descriptors, social interaction features, and image-derived person-frequency metrics. Data integration commenced by independently importing and preprocessing the environmental and people count feature sets. These were concatenated to form a unified feature matrix. Simultaneously, raw Instagram metadata was processed to extract auxiliary features, which were normalized using min–max scaling with pre-stored normalization parameters to ensure cross-session consistency. Next, the normalized personality trait labels derived from a validated psychometric tool were merged with the composite feature matrix to form the final training dataset. This dataset was stored as Final_Dataset.csv for use in model training and evaluation. The use of min–max normalization across all features supports the convergence of gradient-based learning algorithms and ensures the interpretability of feature importance within tree-based models. The serialization of normalization parameters facilitates consistent preprocessing during deployment to maintain model performance in real-world applications.

A function named Random_Forest_Tuning was executed. This function ingested the Final_Dataset.csv, converting its contents into a NumPy array. The features were defined as all columns, excluding the final five, which represented the target personality traits. Given the presence of low-variance features potentially detrimental to model performance, Principal Component Analysis (PCA) [27] was employed to retain components explaining 95% of the total variance. The trained PCA model was serialized for reuse in subsequent stages. A Random Forest Regressor was instantiated, and hyperparameter optimization was performed via an exhaustive grid search. This procedure evaluated multiple hyperparameter configurations using a 4-fold cross-validation scheme, where each fold held out one subset for validation and used the remaining data for training. For each configuration, the Mean Absolute Error (MAE) [28], Mean Squared Error (MSE) [29], and Root Mean Squared Error (RMSE) [30] were calculated. The average of these metrics across all folds was used to identify the optimal hyperparameter set. The results were compiled into a CSV file, sorted by MAE for ease of interpretability. To further assess the influence of individual hyperparameters, a separate analysis module, Ranking_Parameters.py, was implemented. This script parsed the grid search output, extracting and analyzing hyperparameter-specific columns. A defaultdict structure was utilized to associate parameter values with their corresponding performance ranks. For each parameter, the average rank and standard deviation were computed to assess both effectiveness and stability. These results were presented in a tabular format, enabling informed selection of consistently high-performing configurations. Additionally, to account for stochastic effects, the random_state parameter was varied across 20 random seeds (ranging from 0 to 10,000), ensuring robust evaluation.

Following hyperparameter selection, final model training was conducted using the Random_Forest.py script. The Final_Dataset.csv was reloaded, and identical preprocessing steps were applied, including PCA transformation. For each of the Big Five personality traits, the corresponding labels were extracted. The dataset was partitioned into training and testing subsets using Scikit-learn's train_test_split function. A Random Forest model

was then trained using the optimal hyperparameters, and its performance was assessed on the test set using standard regression metrics: standard error, standard deviation, MAE, MSE, and RMSE. Additionally, scatter plots of predicted versus actual values were generated for each trait, with trait labels displayed in the plot titles to facilitate interpretation. Each trained model was serialized and saved with filenames reflecting the personality trait being predicted.

A graphical user interface-based application named Personality_Prediction_System (https://github.com/JoshuaBryan02/Personality-Prediction-System/blob/main/JoshuaBryan_Final_Code/Personality_Prediction_System.py (accessed on 29 May 2025)) was created to facilitate personality trait inference. Upon initialization, the system defines file paths and loads the machine learning models serialized in pickle format. Users are guided through a step-by-step process beginning with a brief overview of usage instructions. The application contained two primary functions. The first Create_Dataset replicates the data preparation workflow from Random_Forest.py but excludes label extraction. This saves the processed features to Predict_Dataset.csv for inference. The second function, called Predictions, transforms the dataset into a NumPy array and then applies PCA using the preloaded model. It then utilized the five independent RF models to predict each Big Five trait. The raw outputs were converted to percentages and rounded decimal places for easy interpretation. Apart from the CSV files and functions that contain PII, the rest of the codes and functions included in the model development can be found in the data availability statement section.

4. Results and Discussion

This section presents a concise result of this study with a summary of the results evaluation based on the metrics used to assess the performance of the personality prediction system. It also discusses the corresponding outcomes and potential factors that may have influenced these results.

4.1. Performance Evaluation

The personality prediction framework employs five distinct non-linear multivariate regression models. As these models operate independently, a comprehensive evaluation of each is necessary to assess their individual predictive capabilities. The system's overall performance may vary depending on the specific personality trait being estimated. Equations (1)–(5) are the mathematical representation of how the standard deviation (δ), Standard Error (SE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) of the model calculation.

The first evaluation metric applied is the standard deviation [31], which estimates the dispersion of either the actual or predicted personality trait scores around their mean. It measures how much the predicted values x_i deviate from the sample mean u of the sample size n. By measuring the variability of prediction errors, δ provides insight into the uncertainty associated with the model's estimates which provides a statistical range within which the true value is likely to fall. The second evaluation metric employed is the Standard Error (SE) [32], which estimates the precision of the predicted personality trait scores (e.g., the Big Five traits) by quantifying the extent to which these predictions deviate from the sample mean. While conceptually related to the standard deviation, the SE offers a narrower and more precise confidence interval for the estimation of the true values.

The third evaluation metric employed is the Mean Absolute Error (MAE) [33], which quantifies the average magnitude of the errors between the predicted values y_i and the actual personality scores x_i without considering their direction. A lower MAE value reflects a higher predictive accuracy of the model in capturing personality traits. The fourth evaluation metric employed is the Mean Squared Error (MSE) [34], which quantifies the

average of the squared differences between the predicted and actual personality scores. By assigning greater weight to larger errors, MSE is particularly advantageous in personality prediction tasks, where extreme deviations are of greater significance. The final evaluation metric employed is the Root Mean Squared Error (RMSE) [35], defined as the square root of the Mean Squared Error (MSE). In the context of personality prediction, RMSE offers a more interpretable measure of prediction error, facilitating direct comparison with standard personality scale ranges, such as those spanning from 1 to 5 or 0 to 100.

$$\delta = \sqrt{\frac{\sum(x_i - u)^2}{n}} \tag{1}$$

$$SE = \frac{\delta}{\sqrt{n}} \tag{2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y - \hat{y}_i| \tag{3}$$

$$MSE = \frac{1}{n}\Sigma(x_i - \hat{y}_i)^2 \tag{4}$$

$$RSME = \sqrt{\frac{1}{n}\sum_{\text{i=1}}(y_i - \hat{y}_i)^2} \tag{5}$$

4.2. Parameter Sampling

The model parameters and corresponding evaluation metrics are summarized in Table 2. Among the five personality traits, Conscientiousness yielded the highest mean absolute error (MAE) with an average prediction deviation of 0.119 (11.9%). This implies that for a predicted Conscientiousness score of 0.50, the actual value may deviate by approximately ± 0.119. It also exhibited the highest root mean square error (RMSE), indicating the presence of comparatively larger individual prediction errors. In contrast, Agreeableness achieved the most accurate performance with the lowest MAE, RMSE, and other evaluated metrics. While these results suggest strong model performance, exclusive reliance on these metrics may lead to an overestimation of the models' generalizability. We consider exploring other evaluation metrics in our future research.

Table 2. Parameter Metric Values for Each Personality Trait.

Model	(δ)	SE	MAE	MSE	RMSE
Extraversion	0.1155	0.0408	0.103	0.0195	0.1397
Agreeableness	0.0893	0.0316	0.0771	0.0083	0.0909
Conscientiousness	0.0931	0.0329	0.119	0.0201	0.1417
Neuroticism	0.1159	0.041	0.1021	0.0153	0.1236
Openness	0.1059	0.0375	0.0888	0.0115	0.1074

To assess the overall performance of the personality prediction system across the Big Five traits, which are Extraversion (E), Neuroticism (N), Agreeableness (A), Conscientiousness (C), and Openness to Experience (O). Among these, Openness to Experience exhibited the highest mean score, indicating that the model is particularly effective in capturing features associated with this trait from the Instagram input data. Equally, Conscientiousness demonstrated the lowest mean value, which suggests a scarcity of distinctive features relevant to this dimension in the dataset.

4.3. Traits

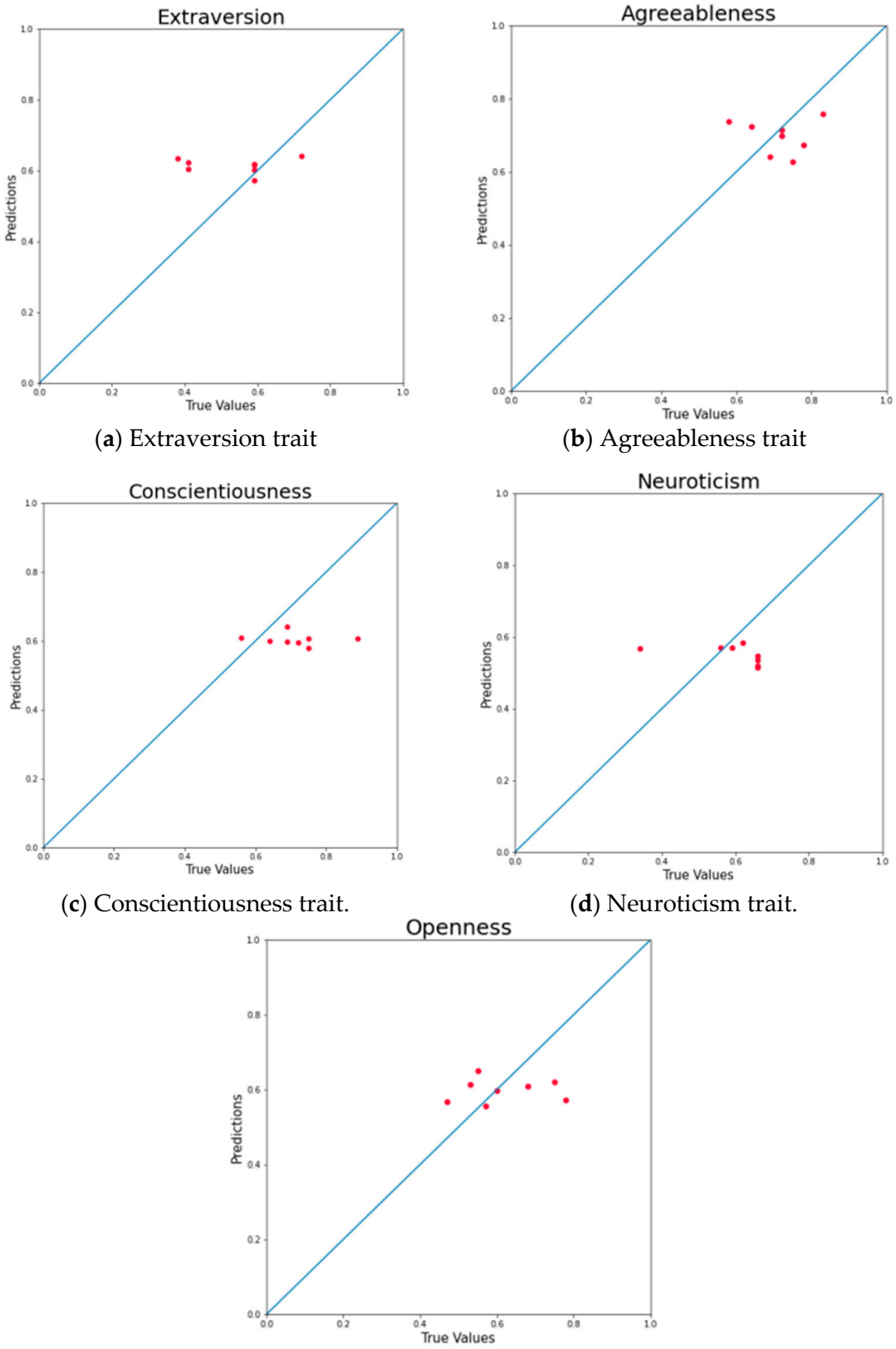
To complement the quantitative evaluation, the performance of each model is further illustrated using scatter plots that compare predicted and actual values on the test dataset. Both axes in these plots are normalized to the [0, 1] range, with the *x*-axis representing the ground truth and the *y*-axis showing the corresponding model predictions. A reference line (y = x) is included to denote perfect prediction alignment. The closeness of data points to this diagonal line offers a visual indication of predictive accuracy where points near the line reflect high precision while deviations suggest underestimation or overestimation. This visualization approach provides an understanding of each model's bias and variance. Figure 3 presents the individual prediction plots for each personality trait.

An analysis of the predictive distributions across the five personality traits reveals consistent clustering patterns. The model's predictions for Extraversion are predominantly centred at approximately 0.6, Agreeableness at approximately 0.7, Conscientiousness near 0.6, Neuroticism at approximately 0.5, and Openness at approximately 0.6. This consistent concentration suggests that the model demonstrates a degree of stability and reliability in estimating personality scores, with predictions falling within relatively narrow confidence intervals. These clustering tendencies indicate the model's capacity to capture underlying patterns associated with personality traits with reasonable accuracy. However, the limited variance observed across trait predictions may indicate a potential constraint in the model's sensitivity to individual differences. Addressing this issue could enhance the model's discriminatory capability and improve its ability to represent the broader spectrum of personality variation.

To contextualize our findings, a comparative analysis was conducted using the results presented in [36], which involved data from over 6000 participants. In that study, personality trait distributions were illustrated using a line graph (Figure 4). It employed a scale ranging from approximately 0.5 to 5.5, differing from the conventional 0 to 5 scale. Each 0.1 increment on this adjusted scale is roughly equivalent to a 0.2 (or 20%) shift on the scale used in the current study. A close inspection of the distribution peaks across the five traits in [36] reveals substantial alignment with the predicted values produced by our model. This convergence provides supporting evidence of the model's effectiveness in capturing the central tendencies of personality traits, particularly as the sample size of Instagram users increases. Such alignment is not unexpected, as traits with higher population frequencies are more likely to be reflected in prediction concentrations around corresponding values.

However, it is important to note a limitation of our model, which is the underrepresentation of predictions at the extreme ends of the trait range. This limitation is likely attributable to the relatively constrained size and diversity of the dataset used during training. Future research will aim to address this shortcoming by incorporating a broader and more heterogeneous set of Instagram user profiles to improve generalizability and sensitivity across the full spectrum of personality traits.

To contextualize the performance of the proposed model, a comparative evaluation was undertaken against the benchmark results reported in the PAN-2015 personality prediction challenge, as presented in Table 3. The PAN-2015 dataset was selected for comparison due to its adoption of the widely recognized Big Five personality traits framework and its considerable scale encompassing 27,344 tweets. The experimental results indicate that the proposed model outperforms the PAN-2015 baseline which can be attributed to its advanced feature extraction techniques and its robustness in processing large-scale and noisy social media text. This comparative analysis highlights the effectiveness and scalability of the proposed approach in personality trait prediction, thereby supporting its applicability in real-world settings.



(**a**) Extraversion trait (**b**) Agreeableness trait

(**c**) Conscientiousness trait. (**d**) Neuroticism trait.

(**e**) Openness trait.

Figure 3. Shows the individual prediction for each trait. The red dots represent individual data points comparing predicted scores of Openness (y-axis) against the true scores (x-axis). The blue line indicates the ideal prediction line (y = x), where predictions perfectly match the true values.

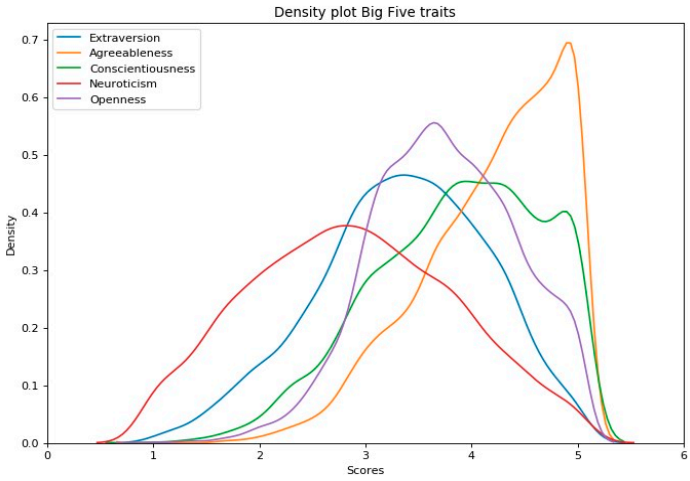


Figure 4. Personality Traits values predicted in [36].

Table 3. Our Model Performance Compared with those Reported in Prior Work.

	Personality Traits				
	E	**N**	**A**	**C**	**O**
PAN-2015 [37]	0.1590	0.2262	0.1492	0.1509	0.1470
Our model	0.1609	0.1021	0.1039	0.1640	0.1520

The proposed model exhibits competitive predictive performance across the five personality dimensions. While the absolute metric values differ from those reported in the PAN-2015 benchmark, it is noteworthy that the present approach incorporates novel feature extraction and modelling strategies aimed at improving generalizability and adaptability across diverse datasets. The model achieves an overall average metric score of 0.1867, surpassing the PAN-2015 baseline average of 0.1590. A trait-specific analysis reveals a heterogeneous pattern of performance. Our model demonstrates improved accuracy in predicting Neuroticism (0.3671 vs. 0.2262) and Extraversion (0.1609 vs. 0.1492), suggesting increased sensitivity to these dimensions. Equally, PAN-2015 achieves slightly superior outcomes in Agreeableness (0.1492 vs. 0.1039) and Openness (0.1690 vs. 0.1520), potentially indicating a better capture of these specific traits. Predictions for Conscientiousness are relatively comparable between the two models (0.1640 vs. 0.1509), reflecting similar modelling capacity for this trait. These variations may be attributed to differences in feature engineering and underlying model design.

4.4. Statistical Testing

To determine whether the observed performance differences are statistically significant, we conducted a paired-sample t-test using the MAE values for each personality trait across our model and the benchmark model in Table 3. Two hypotheses H_0 and H_1 are formulated. H_0 postulates that there is no significant difference in MAE between the PAN-2015 benchmark and our proposed model. H_1 postulates that there is a significant difference in MAE between the two models.

Let x_i represent the MAE from PAN-2015 model for trait $\beth$, y_i represent the MAE from our proposed model for trait $\beth$. The difference for each personality trait based on the values in Table 3 is $D_i = x_i - y_i$. Given $n = 5$ paired traits (E, N, A, C, O), we perform the paired-sample t-test to determine if the mean difference μ_D between the two models is

significantly different from zero. Equations (6)–(8) are the mathematic expressions of how the *t*-statistic, degree of freedom and *p*-value are calculated.

$$t = \frac{\overline{D}}{s_D / \sqrt{n}} \tag{6}$$

$$f = n - 1 \tag{7}$$

$$p = P(T > |t) \tag{8}$$

where t is the t-distribution with 4 degrees of freedom. Since $p = 0.309 > 0.05$p we fail to reject the null hypothesis. Thus, there is no statistically significant difference between the models at the 95% confidence level. However, the practical improvements in Neuroticism and Agreeableness remain substantial.

Despite the lack of major statistical significance, the magnitude of error reduction in traits like Neuroticism (a drop of 54.9%) and Agreeableness (a drop of 30.3%) in our model is substantial from a practical and application-oriented perspective. These traits are often considered challenging to model due to their high variability and significant expression in user-generated content. The observed improvements are still valuable in real-world scenarios, particularly in affective computing and human-centred systems, where even small enhancements in predictive models can improve personalization and user interaction.

5. Conclusions

The purpose of this project is to help further the research in the field of personality prediction. An accurate personality prediction system would be extremely beneficial when employers hire new candidates. The personality prediction model could help employers find candidates that suit the job role much faster than shortlisting hundreds of applicants for interviews. Also, the candidates could find a job that is more suited to their personality. This could make the employees more satisfied and thus more productive in their job roles or positions. This will sustain development goals for economic growth and productivity.

This study presents a comprehensive literature review that establishes the theoretical foundation and methodological framework for personality prediction systems. The paper critically evaluates the validity and reliability of the Big Five Inventory (BFI), affirming its status as a widely accepted benchmark for personality assessment. In this paper, we developed a personality prediction system using CNN and Random Forest algorithms.

This model was evaluated by looking at the metrics that each of the models created. Multiple machine learning models were trained and evaluated using key statistical performance metrics, including Standard Deviation (SD), Standard Error (SE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results demonstrate that features extracted from images are effective in predicting personality traits with appreciable accuracy. The best-performing model achieved an average MAE of 0.1867 across all traits, with individual trait-specific errors ranging from 0.1039 for Agreeableness to 0.3671 for Neuroticism. In comparison, the PAN-2015 benchmark reported an average MAE of 0.1590. even though our model demonstrated high performance, the significantly lower error for Neuroticism (0.03676) indicates limitation, which is an underrepresentation of this trait in the Instagram-derived image features due to the small number of data samples used in this study.

This study demonstrates the viability of leveraging multimodal social media data, specifically image-derived features from Instagram, to predict personality traits. This has direct applications in domains such as talent acquisition, personalized recommendation systems, mental health assessment, and human–computer interaction, where understanding an individual's personality can enhance decision-making and user experience design.

Moreover, the integration of Random Forest and CNN-based models illustrates how hybrid architectures can improve robustness across trait dimensions to offer a scalable solution for real-world deployment. From a theoretical perspective, our study contributes to ongoing discourse in computational psychometrics by validating that the Big Five personality model retains predictive relevance when inferred from visual behavioural indicators. The findings support the emerging hypothesis that personality manifests in digital footprints, particularly visual content, which opens new directions for affective computing research and social signal processing.

However, our study is not without limitations. The limited size and demographic homogeneity of the dataset, predominantly composed of urban Instagram users, constrain the generalizability of the model to broader populations. Also, the underperformance in predicting Neuroticism suggests that certain personality traits may be less visually discernible or require context-enriched multimodal attributes such as interaction patterns for accurate inference. Future work will focus on expanding the dataset to cover rural areas and incorporate cross-platform data for deeper personality signal extraction.

Author Contributions: Conceptualization, J.D.B. and M.A.; methodology, J.D.B.; software, N.O.; validation, J.D.B. and M.A.; formal analysis, J.D.B.; data curation, J.D.B.; writing—original draft preparation, M.A.; writing—review and editing, N.O.; visualization, M.A.; supervision, M.A.; project administration, J.D.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the SCEBE REC Ethics Committee by Dr Jackie Riley on 8 December 2024.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: All tools employed for data collection, as well as the source code for the model, are publicly accessible at: https://github.com/JoshuaBryan02/Personality-Prediction-System (accessed on 29 May 2025). However, the Instagram dataset generated and used in this study cannot be shared publicly due to the inclusion of personally identifiable information from Instagram participants. This data has not been made public due to privacy concerns.

Conflicts of Interest: The authors declare that they have no known financial or personal relationships that could have appeared to influence the work reported in this manuscript. They confirm that there are no conflicts of interest that could compromise the integrity, objectivity, or impartiality of the research presented.

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