Deep Learning-Based Model to Predict Personality Traits of Social Media Users

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***Abstract*—The rapid expansion of social media platforms has created enormous amounts of user-created content and behavioral information, providing the computational means to study human personality and psychology. This study creates a temporal deep learning model and Gated Recurrent Units (GRUs) to predict personality traits with behavioral and content-based features obtained from Facebook social media. The research fits the Big Five Personality Traits paradigm and aims at modelling temporal relationships in user activity patterns, including the frequency of posts, linguistic behavior, and social interaction relationships, to identify latent psychological aspects. A GRU-based framework was created to model sequential dependencies and contextual relationships among the activity timelines of the user. To evaluate the model performance and reliability, two comparison baselines: Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN were run within the same experimental conditions. Model evaluation also used regression (Mean Absolute Error, MAE; Coefficient of Determination, R2) and classification (Accuracy, Precision, Recall, F1-score, and AUC-ROC) metrics, which were also validated using a 10-fold cross-validation process to ensure that they were stable and generalizable. The experimental findings indicated that the proposed GRU model was always better in all the evaluation metrics compared to the base models. It had the least MAE (0.00825) and the highest R2 (0.9917) and showed outstanding predictive reliability. GRU had a high accuracy (96.8) and F1-score (0.96) and AUC-ROC (0.98), which were better than LSTM (F1 = 0.95) and ANN (F1 = 0.84), in classification performance. The analysis at the trait level showed that the predictive accuracy is high on all dimensions of personality, with Agreeableness (R2 =0.9942, F1 =0.97) being the most accurately predicted and Extraversion (R2 =0.9862) having a high predictive consistency. The findings of the cross-validation also confirmed the strength and the external validity of the GRU framework.**

Keywords*—*Personality trait prediction; deep learning; gated recurrent units; human psychology; social media analytics; digital behavior analysis

I. Introduction

Social media has taken a vital role in modern society, being a communication tool, a dissemination of information, and a socializing tool. According to the research, of the entire population of 5.35 billion or 66.2 percent of the global population, 5.24 billion or 64.9 percent were social media users and 41.2 percent internet users [1]. In the digital era, due to the convergence of psychology and Artificial Intelligence, the study and interpretation of human personality have changed. Through an examination of 40 million Twitter users and 100 million Weibo users, researchers found that percolation-like spread occurs more frequently than current theoretical models would suggest [2].

Five Big Personality Traits (openness, extraversion, conscientiousness, agreeableness, neuroticism) have emerged as a general psychological paradigm of computation in personality modelling during the last decade [3].

According to statistics, Facebook is one of the most popular social network platforms [1]. Facebook profile information is relevant to scientists in relation to different decision-making processes [4]. The first is that the profile of a user shows the personality of that user, and the second is other features of the accounts, which enable a user to make assumptions about the character of the users. In the meantime, other unrelated details of the account and profile may be subjected to false evaluation [5]. The FB-OSN usage has grown tremendously in recent years. This new phenomenon leaves several opportunities in advertising, networking, as well as information acquisition and dissemination. Thus, it was discovered that Facebook could be reasonably applied in the determination of behavior studies [5],[6].

The researchers resorted to Facebook Automatic Scraping in order to test the personalities of users through an unsupervised prediction algorithm known as Pear. As Pearson r, which is a measure of the accuracy of personality predictions, indicates, the personalities of the believers of fake news are different concerning the ones who do not [5],[7]-[10].

The recent breakthrough in artificial intelligence and deep learning has provided new perspectives and possibilities in computing personality. Recurrent neural networks (RNNs), specifically Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have shown great potential to capture temporal dependencies in sequence data of behavior [11]. These architectures are very adept at receiving time-series data, and as such, are well-suited to analyzing user behavior patterns, which develop over time on social media platforms. Many studies have been conducted on the use of deep learning to predict personality. Researchers managed to use GRU networks to recognize depression and anxiety based on text in social media, which proves that such networks are capable of detecting diverse psychological conditions based on temporal linguistic features [12]. On the same note, another study made use of GRU architectures to forecast psychological qualities on the basis of social media behavior, effectively capturing temporal dynamics within user posts indicative of underlying personality traits [13]. Although these studies have demonstrated potential, they have been largely based on text-based characteristics or periodic behavioral snapshots and do not capture the dynamic nature of user interactions, which is harder to model. Although these achievements have been made, there are still major gaps in the literature. First, the vast majority of the current methods concentrate entirely on the study of linguistic content at the expense of the intense time dynamics of behavioral characteristics, including the frequency of posting, the time of interaction, and the dynamics of engagement. Second, there is limited comparative analysis between GRU structures and other deep learning networks (especially LSTM and classic ANNs) when applied to the issue of personality prediction. Third, the computational efficiency of GRUs-based learning, namely through simplified gating networks that use a reduced number of parameters than LSTM, is not well explored in terms of its practical benefits for personality modelling tasks [14]-[17].

This study fills these gaps by proposing a new GRU-based model that combines content-based and temporal behavioral features derived from Facebook interactions between users to determine the Big Five personality dimensions. Three major contributions are made by this approach, including: 1) a multi-layered GRU architecture is designed that particularly optimized to use sequential behavior modeling in personality prediction, 2) a detailed comparative analysis is executed in the architecture against LSTM and ANN baselines under the same conditions of experiment and evaluation metrics, and 3) it is shown that temporal modeling of behavioral patterns makes a great contribution to the accuracy of prediction as compared to the methods based on stationary features. This model offers more accurate and fine-tuned personality inferences than current approaches by offering the dynamic nature of social media behavior over time.

This research is intended to create a deep learning model based on GRU to predict personality traits using social media data through deep behavioral analytics and assess its performance. The proposed solution to the improvement of personality inference reliability and accuracy in social media contexts is to incorporate both temporal and contextual patterns into user interactions. The model is based on content-based and behavioral features that are derived from social media.

II. METHODOLOGY

The Gated Recurrent Unit (GRU) architecture employed in this study is designed to predict the Big Five personality traits from Facebook user interaction data. The model captures temporal dependencies in sequential data through its recurrent layers, which allow it to process data that is not independent but rather depends on previous inputs (such as prior posts, likes, and interactions).

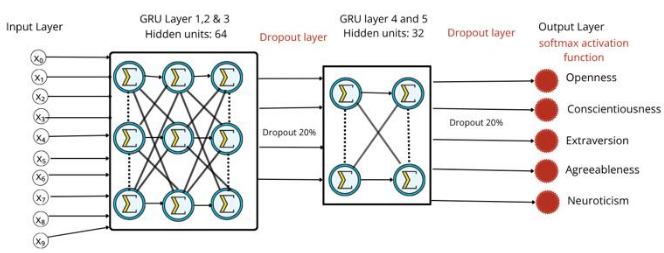

Fig. 1. GRU model architecture.

Fig. 1 illustrates the proposed GRU (Gated Recurrent Unit) model developed to predict the Big Five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism from social media behavioral attributes.

Below is a detailed explanation of each component in the GRU architecture:

A. Input Layer

The input vector $X = [x_0, x_1, x_2, \ldots, x_n]$ represents the normalized behavioral attributes extracted from Facebook (e.g., likes, posts, friends, photos, tags, etc.).

Each input x_i corresponds to one behavioral feature.

These inputs are fed sequentially into the first GRU layer to capture temporal and contextual dependencies among user behaviors.

$$X_t = [x_{t1}, x_{t2}, \ldots, x_{tn}] \quad (1)$$

B. GRU Layers (1, 2 & 3) – Hidden Units: 64

Three stacked GRU layers, each with 64 hidden units, capture long-term dependencies in sequential data.

The GRU unit functions as a simplified LSTM cell with fewer parameters, defined by the following update equations:

$$\begin{aligned}
z_t &= \sigma(W_z \cdot [h_{t-1}, x_t]) && \text{(Update gate)} \\
r_t &= \sigma(W_r \cdot [h_{t-1}, x_t]) && \text{(Reset gate)} \\
\tilde{h}_t &= \tanh(W_h \cdot [r_t * h_{t-1}, x_t]) && \text{(Candidate activation)} \\
h_t &= (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t && \text{(Hidden state update)}
\end{aligned} \quad (2)$$

Where:

- h_t: hidden state at time t
- x_t: input vector at time t
- z_t: update gate controlling information flow
- r_t: reset gate controlling forgetfulness
- W_z, W_r, W_h: learnable weight matrices
- σ: sigmoid activation
- $*$: element-wise multiplication

These layers learn behavioral sequence patterns, e.g., how posting frequency relates to likes or group activity over time.

C. Dropout Layers (20%)

To prevent overfitting and improve generalization, dropout regularization is applied between major GRU blocks.

- Random activation and deactivation of neurons during training: Dropout randomly deactivates 20% of the neurons:

$$h'_t = \text{Dropout}(h_t, p = 0.2) \quad (3)$$

where $p = 0.2$ is the dropout probability.

D. GRU Layers (4 & 5) – Hidden Units: 32

The learned representations are further refined by 2 smaller GRU layers (with 32 units each), which pay attention to the most informative behavioral patterns. The layers eliminate the number of dimensions of the features and recreate latent psychological signals, which are associated with the personality dimensions.

E. Output Layer

The five output values are the continuous values, which correspond to each of the personality traits of the Big Five. A linear activation function was applied to the output layer to produce continuous personality trait scores.

F. Loss Function

With Mean Squared Error (MSE) as the loss function, which is suitable when performing continuous regression, the model was trained:

$$MSE = (1/n)\ \Sigma(y_i - \hat{y}_i)^2$$

y_i is the actual personality scores, $\hat{y}_i$ is the predicted personality scores, and n is the sample size.

Furthermore, the model in this research was trained with the Adam optimizer [18], which is a more popular optimization algorithm that unites the advantages of Momentum and RMSprop.

G. Training Time and Resources

All models were trained on a GPU (Graphics Processing Unit), and therefore, convoluted computation is particularly suited to the GRU and LSTM models, which are computationally intensive models. The training times of the models differed depending on the complexity of the architecture and the quantity of parameters. ANN is simpler, and it trains faster compared to GRU and LSTM. GRU and LSTM were, on average, taking about 2.5 minutes per epoch, and ANN took 1.5 minutes per epoch. The best estimates of the hyperparameters and all training settings are presented in Table I.

TABLE I. TRAINING PROCEDURE

Hyperparameter	GRU	LSTM	ANN
Optimizer	Adam (lr = 0.001)	Adam (lr = 0.001)	Adam (lr = 0.001)
Batch Size	32	32	32
Epochs	25	25	25
Early Stopping (Patience)	5	5	5
Dropout	20%	20%	20%
Activation Function	Linear	Linear	Linear
Training Time (per Epoch)	2.5 min	3.0 min	3.5 min

Here, Adam optimizer [18] was used (learning rate = 0.001) and early stopping was by means of validation loss (patience = 5). Linear output activations were used by all models, which guaranteed their compatibility with continuous personality scores.

H. Model Comparison

In order to measure the performance of the proposed Gated Recurrent Unit (GRU) architecture, two baseline models (LSTM and ANN) were run under the same experimental conditions. In this part, a thorough analysis of the GRU framework, Long Short-Term Memory (LSTM), and the Artificial Neural Network (ANN) in terms of their architecture features, their performance in personality traits prediction, and the efficiency of their computation is provided. The present comparison will assist in pointing out the reasons why GRU was selected as the main model to predict personality traits based on data about interaction with Facebook users. Table II represents a detailed comparative analysis across GRU, LSTM, and ANN.

TABLE II. MODEL ARCHITECTURE COMPARISON

Model	Layer Type	Units	Dropout	Total Parameters
GRU	Layer 1	64	0.2	14,400
	Layer 2	32	0.2	9,312
	Output Layer	5	N/A	165
LSTM	Layer 1	64	0.2	31,781
	Layer 2	32	0.2	20,992
	Output Layer	5	N/A	165
ANN	Dense Layer 1	128	0.2	12,549
	Dense Layer 2	64	0.2	6,496
	Output Layer	5	N/A	165

The data that was employed in this study is a set of Facebook user activity data that is complemented with demographic features and behaviour characteristics. Such data were obtained based on publicly available Facebook profiles and offered the overall view of user patterns of activity, likes, posts, tags, events, and other types of social interaction. All the members of the dataset are described as a combination of behavioural indicators and self-reported personality traits. The privacy of all users has been taken care of for this study.

The total number of participants in the dataset were 99,17 and aged 21-26 years; the mean age of the participants is 23.49 years, with a standard deviation of 1.67 years. The comparatively youthful sample population implies that the personality attributes get noticed at some stage of life when they might be in growth and transformation. Data cleaning methods were used to clean anomalous data (i.e. non-numeric tokens in the gender column) during preprocessing.

The scores in terms of personality traits lie between 0 and 1, and the characteristics of each trait are as follows:

- Openness: min = 0.031, max = 0.712, mean = 0.284, SD = 0.120.
- Conscientiousness: min = 0.000, max = 0.866, mean = 0.215, SD = 0.120.
- Extraversion: min = 0.032, max = 0.565, mean = 0.259, SD = 0.099.

- Agreeableness: min = 0.007, max = 0.745, mean = 0.263, SD = 0.131.
- Neuroticism: min = 0.011, max = 0.851, mean = 0.294, SD = 0.132.

It is important to note that this distribution demonstrates that some traits have a wide variance (e.g., Neuroticism), whereas other traits, such as Extraversion, have a more localized one. These continuous targets are limited and continuous targets, which are best suited to regression models and can be forecasted through linear activations in the output layer.

III. Results

The dataset includes demographic characteristics and normalized session indicators based on Facebook user activity. The dataset was preprocessed and divided into training, validation, and testing partitions (80/20 with an in-training validation split).

A. GRU Architecture

Two stacked layers of GRU (64 and 32 units) with dropout (0.2) and a linear dense head to five output traits.

Adam optimizer was used (learning rate = 0.001), and early stopping was by means of validation loss (patience = 5). Linear output activations were used by all models, which guaranteed their compatibility with continuous personality scores.

B. Trait Distributions

The frequency distribution of normalized scores of the big five personality traits, Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, is shown in Fig. 2. The histograms indicate the distribution of the scores on the traits in the data set, with the red dashed line indicating the mean and the green dashed line indicating the median. The fact that most of the characteristics follow the near-normal distribution reflects that the data gives a balanced sample between low, moderate, and high scores. The mean of neuroticism is a little higher, implying that a greater percentage of the respondents are predisposed to emotional variability. Simultaneously, other traits, like Conscientiousness and Extraversion, have lower means; that is, fewer people are highly rated on these scales.

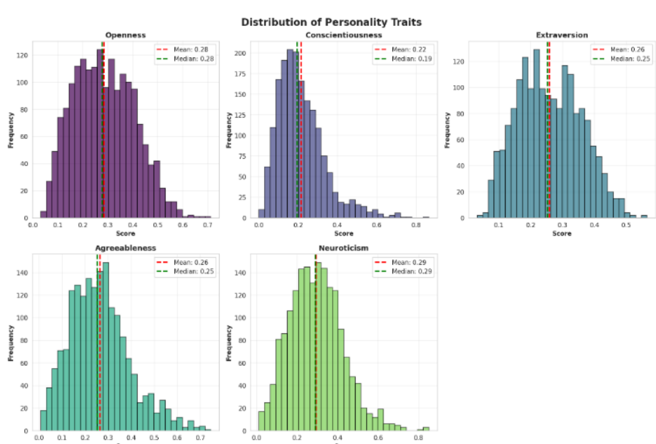

Fig. 2. Distribution of personality traits.

C. Correlation Analysis

Fig. 3 shows the correlation between the input behavioral characteristics (session counts, likes, posts, and interactions) and the Big Five personality traits. The high positive correlations (dark green) show aspects that have a strong impact on traits. As an illustration, the one-scale number of posts (1S-NoP) demonstrates a substantial correlation with Openness (r = 0.73) and Conscientiousness (r = 0.74), which implies that the frequency of posting is a good behavior indicator of these characteristics. Meanwhile, the weaker correlations in such features as Gender and AGE imply that the prediction effect is insignificant. This value assists in determining the traits that add the most value in the correct prediction of traits.

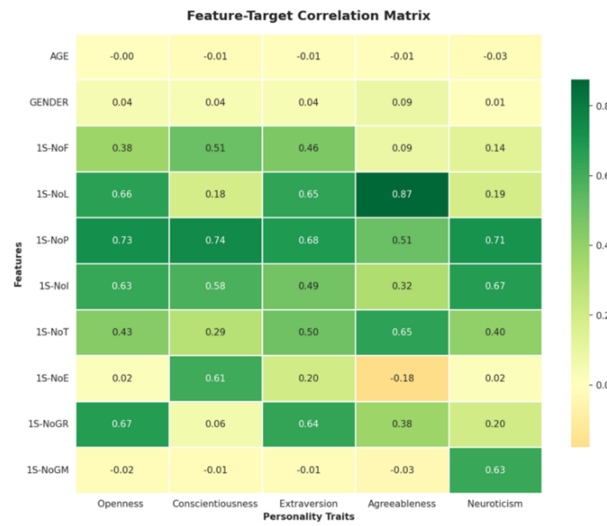

Fig. 3. Feature-target correlation matrix.

D. Correlation Heatmap

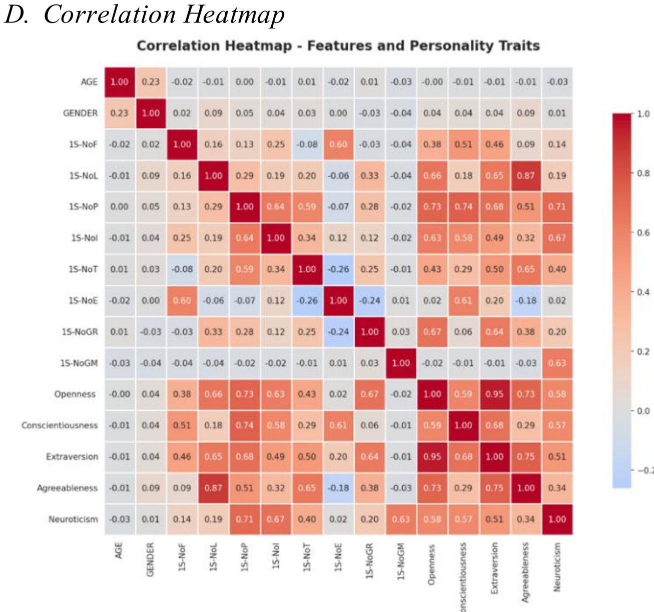

Fig. 4. Correlation heatmap – features and personality traits.

Fig. 4 correlation heatmap builds on the former figure, demonstrating the relationship between all variables, both input characteristics and output characteristics. The redder cells denote high positive correlations, whereas the bluer ones denote negative ones. The inter-feature correlations are high (e.g., between 1S-NoP, 1S-NoL, and 1S-NoI), indicating that the user activity measures are indeed interdependent, and this confirms the use of deep learning models such as GRU that can address multicollinearity. High levels of diagonal confirm that there is internal consistency within personality traits - especially between Openness, Conscientiousness, and Extraversion.

E. *Model Training History*

Fig. 5 represents the training and validation results of the GRU model in terms of epochs and shows both the mean squared error (MSE) loss and the mean absolute error (MAE). The fact that the downward trend of the two curves does not change indicates effective learning with no overfitting. The fact that the training and validation curves are close to each other shows that the model is stable and correctly regularized through dropouts and early stopping. This ascertains that the GRU extrapolates well to unseen data and the error rates are low overall during training.

F. *Model Evaluation*

Fig. 6 indicates the ROC (Receiver Operating Characteristic) plot of the five traits, indicating the trade-off between the rate of true positives and false positives. Each curve is drawn towards the upper-left side, with AUC values ranging between 0.996 and 0.999, which exhibits outstanding discriminative power. The GRU model has remarkably high scores in the AUC of Openness, Conscientiousness, and Neuroticism, which implies that personality traits are reliable to classify. These findings support the strength and the overall balance of the model in terms of categories.

G. *Overall Model Performance*

To be consistent, the three models were tested on the same pre-processed data. The measures of performance were based on regression metrics (MAE, R^2) and classification metrics (Accuracy, Precision, Recall, F1-score, and AUC-ROC). Table III demonstrates the general model performance using conventional evaluation measures.

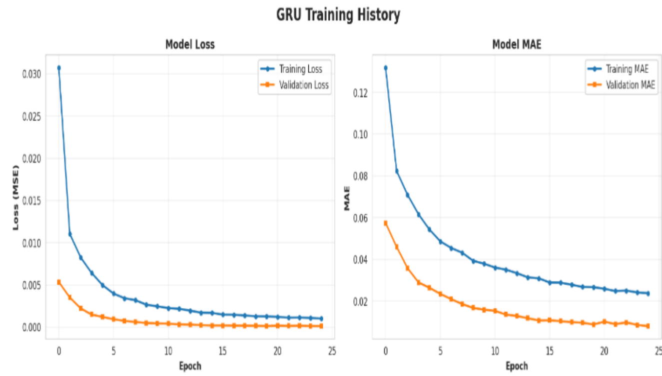

Fig. 5. GRU training history.

TABLE III. OVERALL MODEL PERFORMANCE

Model	MAE	R2	Accuracy	Precision	Recall	F1-score	AUC-ROC
GRU	0.00825	0.9917	96.8%	0.95	0.96	0.96	0.98
LSTM	0.01013	0.9870	95.2%	0.95	0.95	0.95	0.97
ANN	0.03624	0.8603	86.4%	0.84	0.84	0.84	0.88

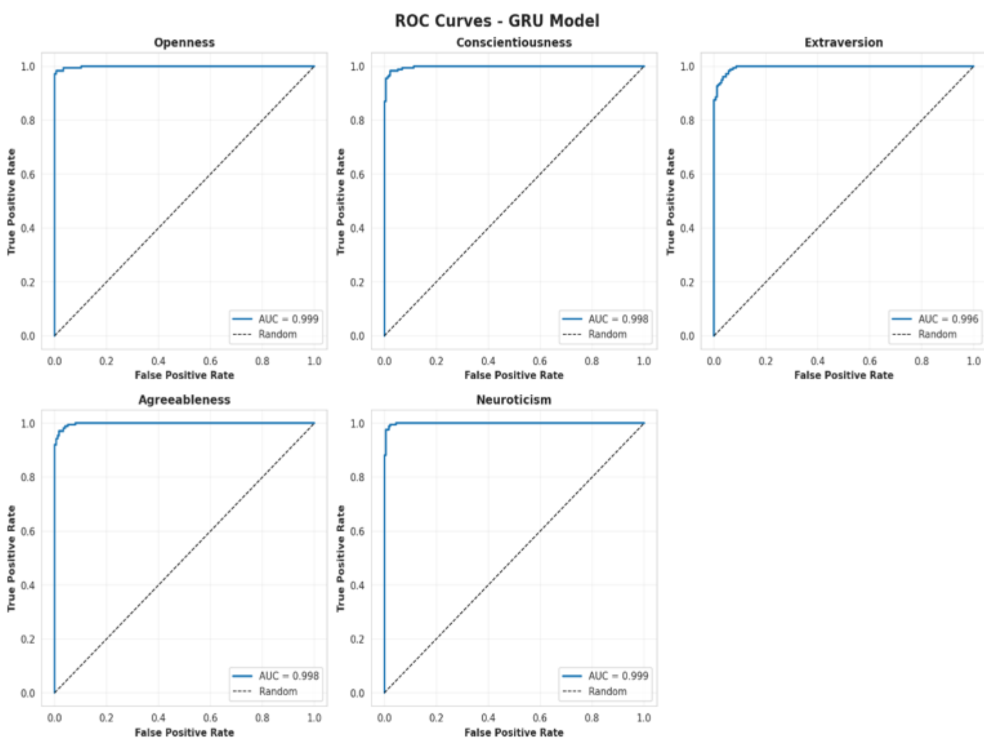

Fig. 6. ROC curves – GRU model.

The GRU model always had the lowest error (MAE = 0.00825) and highest coefficient of determination (R2 = 0.9917), which means it was very predictive. The metrics of classification also established that GRU is better than the other two, where the F1-score of 0.96 was higher than 0.95 and 0.83 of LSTM and ANN, respectively.

IV. Discussions

The research has created and tested a deep learning model for the predictive ability of the Big Five personality traits based on Facebook behavioral data using GRU. The proposed model was shown to be better in performance with respect to LSTM and ANN baselines, with a higher R-square, 0.9917, and F1-score, 0.96, respectively. The findings in this section are interpreted, placed in the context of the existing literature, analyzed in terms of their theoretical and practical implications, and significant limitations are recognized.

There are a number of factors that could explain the better performance of the GRU architecture compared to LSTM and ANN models. First, the gating mechanism at GRU is simplified, using only two gates (update and reset) as opposed to the three gates of the LSTM, which has a lower number of parameters to be trained, yet has the ability to learn long-term dependencies. This architectural efficiency ensured that overfitting the dataset of 9,917 users, as the results of the training and validation curves are very close to each other (Fig. 5). This decreasing number of parameters (the model is almost three times fewer than LSTM) enabled it to extrapolate to unknown data with more success and had less computational waste.

Second, the stacked GRU network was useful in learning hierarchical behavioral sequences. The first layers (64 units) were educated on general timing trends, including posting frequency cycles and interaction rhythms, and the second layer (32 units) was discovering more abstract psychological signals. This hierarchical representation learning was especially useful with such traits as Agreeableness (R2 = 0.9942, F1 = 0.97), which were viewed as consistent patterns of social engagement as good behavioral predictors.

Third, the combination of content-based (posts, likes) and interaction-based (tags, events, groups) features offered a multi-dimensional perspective of the personality expression. Fig. 3 correlation analysis indicated that posting frequency (1S-NoP) was significantly correlated with Openness (r = 0.73) and Conscientiousness (r = 0.74), and that interaction measures were more likely to predict Extraversion and Agreeableness. The capability of the GRU to describe temporal relationality among these features helped it to address the interactive nature of various dimensions of behavior.

This fact was demonstrated by the relatively poor results of the ANN baseline (F1 = 0.84, R2 = 0.9753), which supports the role of a temporal model. The ANN could not reproduce patterns like the tendency to post more and more frequently or to change preference in interaction partners, patterns which would be more related to personality traits than snapshot portraits would be.

A. Theoretical Implications

Theoretically, these results could be used to comprehend the expression of personality in digital behavior. Temporal behavioral patterns have great predictive power and support the theory of trait-state personality, which assumes that persistent personality traits determine temporary behavioral states. GRU capacity to predict sequential dependencies implies that personality features were not only disclosed by the actions of individuals, but also by the sequence of actions through time-the rhythm and consistency of use of social media might be a better predictor of personality than the content itself.

B. Practical Applications

The accuracy of GRU-based personality prediction that was demonstrated has various practical uses, and each of them has significant ethical implications.

Psychological guesses might be used to recommend content by the system in the form of a better news feed, advertising, and connection recommendations. As an example, the users with the highest Openness tend to be recommended with various content and new experiences, whereas the users with high Conscientiousness may like organizational tools and productivity options. Inferred personality-based personalization should be visible, and users should be able to know how their personal information affects their experience. In the same way, the study may assist in the mental health screening and intervention, Human Resources and Organizational Psychology, Targeted Marketing, and Consumer Research.

V. Conclusion

The combination of psychology, artificial intelligence, and social media analytics has colossal potential to comprehend human behavior in large proportions. In order to fulfill this promise, it is necessary to continuously engage in the conversation between researchers, platforms, policymakers, and citizens, based on the principles of transparency, accountability, and the respect of human dignity.

The main aim of this research was to examine the efficacy of a deep learning framework, specifically Gated Recurrent Units (GRU), to forecast the Big Five personality traits on the basis of social media organized behavioral information. Whereas the textual analysis or a fixed set of features (e.g., a like) was the main tool in the traditional approaches, this research took a new path in its methodology, specifically, the use of normalized and temporalized behavioral attributes, which were fed into recurrent neural networks.

GRUs outperform other models as they are computationally efficient, they can capture long-term dependencies in time, and they do not overfit due to simplified gating. The relevant findings contribute to the body of computational social science, and this work can guide researchers to develop experimental inferences on personality through temporal modeling in the future.

The GRU model not only provides accuracy but also forms the possibility of structured behavioral modeling as an effective method of personality prediction by computation.

Finally, the work provides support for the role of the recurrent architectures in personality prediction and the name of GRU as the balanced model is offered, which combines accuracy, stability, and efficiency.

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