Mapping Personality Traits through Keystroke Analysis

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Abstract: Personality can be defined as a set of psychological features that may determine how to think, act, and feel, as well as may directly influence an individual's interests. The Big Five model is widely used to describe the main traits of the personality of an individual. This study aims to develop an approach to identify personality traits from keystroke dynamics data using neural networks. We developed a non-intrusive approach to collect keystroke dynamics data from the users and used a self-assessment questionnaire of personality to identify Big Five personality traits. Experiments showed no evidence that the exclusive use of keystroke dynamics characteristics can provide enough information to identify an individual's personality traits.

1 INTRODUCTION

Affective computing is a branch of intelligent computing that deals with the properties of users' personality and emotion in computational systems. Its goal is to identify, model, and implement human emotion in a computational format, giving the system the ability to react based on the user's personality. The personality can be defined as a set of psychological properties capable of determining the individuality of someone based on the way he thinks, acts, and feels (Pervin et al., 2004), influencing the behavior (Carver, 2000), being public knowledge, although nobody knows how to describe in a precise way (Allport, 1961). The personality is known as a relatively stable characteristic in an individual that can be modified, but is relatively stable for about 45 years, starting on the adult phase (Nunes et al., 2010) and is a determining factor on the human behavior. The personality is capable of directly influencing the interests of an individual, making the computational identification and modeling of personality a prerequisite for the creation of new applications, system models, and customizable virtual environments (Stathopoulou et al., 2010).

Computational systems are developed to perform a uniform behavior, independently of the user interacting with it, using just the the input data. We may enable computer systems to analyze the user's input data not just as a source of raw information but also as a source of metadata capable of identifying individuals and a group of users with similar behaviors and interests. Doing so opens the doors to the construction of a new class of computer systems, aimed at personalizing the user experience, adapting itself according to each individual's particular characteristics.

Keystroke dynamics is the process of extracting an individual's biometric pattern using the manner and rhythm at which he types characters on a keyboard (Shepherd, 1995). The data extracted from keystroke dynamics can be used for authentication, identification, and analysis of the user's particular characteristics. This biometric pattern is available from any conventional computer keyboard and can be easily extracted when looking for the data from a key holding time and up time. Hold time, which is often found in the literature as dwell time or down time, represents the time interval between pressing and releasing the same key on a keyboard. Up time, also described as flight time or up-down time, represents the time elapsed between releasing the current key and pressing the next one. From a dataset containing these two characteristics, it is possible to determine the pattern of typing of an individual, and from this pattern seek the correlation with the characteristics of his personality.

The demand for giving the computer the ability to identify, interpret, and respond appropriately to a user depending on his characteristics is an important step in the evolution of human-computer interaction. Previous studies (Khan et al., 2008; Nahin et al., 2014;

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Solanki and Shukla, 2014) state that emotions have a significant role in this process.

Khan (Khan et al., 2008) developed a tool to extract individuals' personality traits through the typing rhythm and mouse usage, basing their experiments on studies that identified that extroverts interact with the interface of computer systems more quickly than an introvert. As a result of his studies, Khan (Khan et al., 2008) concluded that it is possible to measure a user's personality through his way of using the keyboard and mouse. In this study, Khan (Khan et al., 2008) used a reduced version of the NEO-IPIP (Neuroticism-Extraversion-Openness International Inventory Item Pool) as a form of self-assessment by the participants. The NEO-IPIP questionnaire is composed of 120 questions and requires between 15 and 25 minutes to be answered. The results obtained by Khan (Khan et al., 2008) for the five personality traits mapped varied between -0.4 and -0.56, which according to the Pearson scale represent "weak" and "moderate" correlations, respectively.

Khanna and Sasikumar (Khanna and Sasikumar, 2010) proposed an approach to detect the emotions of computer users from data obtained from the use of a conventional keyboard. The approach is based on the study of more specific characteristics, such as typing speed, mode, standard deviation, amount of backspaces, and others, obtained from the analysis of the hold time and up time of each individual. This study included 300 participants (45% women and 55% men), aged between 21 and 41 years, and obtained up to 88.88% and 89.02% success rates in the identification of positive and negative emotions, respectively.

The use of keystroke dynamics data as a source of information for detecting emotional state was also the subject of a study carried out by Epp, Lippold and Mandryk (Epp et al., 2011), which, with only 12 participants (10 men and 2 women), mapped 15 distinct emotional states with success rates ranging between 77.40% and 87.80%. Zimmermann (Zimmermann et al., 2003) present an approach similar to Khan (Khan et al., 2008) when simultaneously using data extracted from the keyboard and mouse, although the studies of Zimmermann (Zimmermann et al., 2003) do not focus directly on personality extraction but on the measurement of mood. His aim is to improve human-computer interaction without worrying if the current mood comes from permanent personality characteristics or something temporary related to the individual's emotional state.

Supporting the usage of keystroke dynamics as a method of extracting user data, Nahin (Nahin et al., 2014) justify that the computer keyboard, even though it is a cheap equipment, still allows communication between humans and computers. In their work, seven classes of predefined emotions were used (joy, fear, anger, sadness, guilt, shame, and disgust) to detect the variation in the behavior of computer users during the process of transition from one emotional state to another. The work developed by them was done so that no additional hardware other than a conventional computer keyboard was needed. To carry out their study, Nahin (Nahin et al., 2014) defined two different approaches: use of predefined text, and; use of free text. Not only was the user's typing rate analyzed, but also an analysis of the text he produced. The data acquisition phase was carried out with only 25 volunteers, whose ages varied between 15 and 40 years, with approximately 45% of the participants being women and 55% men. As a result of their work, Nahin (Nahin et al., 2014) achieved between 60% and 87% accuracy in identifying those emotions.

Solanki and Shukla (Solanki and Shukla, 2014) also developed an approach to extract the emotional state of individuals using data from the typing rhythm and its correlation with self-assessment questionnaires. In their work, Solanki and Shukla (Solanki and Shukla, 2014) aimed to identify the emotional state based on the use of a conventional computer keyboard, focusing on identifying emotions: confidence, sadness, happiness, tiredness, nervousness, and anger. As well as done by Nahin (Nahin et al., 2014), their work involves two approaches: use of predefined text, and; use of free text. Both experiments obtained good results in identifying the selected emotion classes, and the use of predefined fixed text was more accurate in identifying most emotions. In another of his studies, Khan (Khan et al., 2015) analyzed 47 individuals to identify programmers' personality through the interaction with keyboard and mouse and the application of self-assessment questionnaires. At the end of his study, Khan (Khan et al., 2015) stated that it is possible to differentiate good programmers from not so good programmers in an objective way by correlating the data produced by them.

To identify characteristics such as gender and age of individuals through the typing rhythm, Plank (Plank, 2018) presented in her work evidence about the strong relationship between the individual's identity and the way he types. Buker (Buker et al., 2019) also shows a similar approach to identify the typist gender through keystroke dynamics, with accuracy higher than 95%. Although these studies can identify characteristics such as age and gender with a high accuracy, no details about the possibility of extracting other characteristics, such as personality traits, through the typing rhythm are presented.

In this work, we aim to classify individual's personality traits based on his keystroke dynamics. A dataset was acquired containing subjects' data from a self-assessment personality questionnaire and their keystroke dynamics. To do that, we used convolutional neural networks with the keystroke dynamics data as input and as output the level of each personality trait of the Big Five model.

2 METHODOLOGY

This study is focused on the analysis of the keystroke dynamics of computer users to identify personality traits. Keystroke dynamics is an automatic, non-intrusive approach with a reduced cost of application. A self-assessment questionnaire, based on the Big Five model for describing personality traits, was used. The objective of this study is to answer two questions:

- Q1: Is it possible to measure how much a certain personality trait is present in the personality of an individual through the typing rhythm?
- Q2: Is it possible to determine which personality traits stand out in the individual's personality through the typing rhythm?

A dataset was acquired, pre-processed, and used to train different neural networks to reach the objectives of identifying an individual's personality traits from keystroke analysis. This section describes the methodology used, divided in three steps:

1. Data acquisition
2. Pre-processing
3. Analysis

The data acquisition step was responsible for acquiring the basic information for the accomplishment of this study. It was done by capturing the subjects' keystroke data and the application of a self-assessment personality questionnaire. In pre-processing step, equalizations and conversions of the obtained data were done to adapt them to each experiment. In the analysis step, we trained different neural networks to classify the individual's keystroke data.

2.1 Data Acquisition

The data acquisition process was completely online, aiming to be accessed by the largest possible number of participants. It was implemented as a web page built to extract the raw data of the participants' typing rhythm from a conventional computer keyboard and then apply the Ten Item Personality Inventory (TIPI) self-assessment questionnaire.

The web page was available for collecting data for 56 days. Of the 177 participants, 56 were female, and 121 were male. Ages ranged between 12 and 46 years, with 24.83 years as the average age of the participants.

The data acquisition process was divided into three steps: contextualization; extraction of the keystroke dynamics, and; extraction of personality traits. Each stage is described in the sections below.

The average session length of a participant on the data acquisition page, including contextualization, was 11.27 minutes. Extraction of the keystroke dynamics and extraction of personality traits steps had an average duration of 1.97 minutes and 1.61 minutes, respectively, which gives us an average duration of 3.58 minutes to perform the two main steps of the data acquisition process.

2.1.1 Contextualization

The first step of the data acquisition process started with presenting the data acquisition objective, a brief contextualization about what the next steps would be and what should be done by the participant in the next steps. A free consent form was presented to guarantee that the participant understood the details about the confidentiality of his information and that he agrees with the purposes for which the data provided by him in the next steps would be used. The text makes it clear the possibility to give up at any time during the data acquisition process.

2.1.2 Keystroke Data Extraction

After the contextualization step, the data acquisition step effectively starts with presenting the predefined text. Participants are instructed to type the text exactly as shown, in a text field, twice in a row.

The text selected for data acquisition was designed in the native language of the participants, so it was not necessary to capitalize letters or add accents. The text contains only a single punctuation symbol, with a simple vocabulary composed of words common in casual speech, with 194 characters.

All care in the text elaboration came from the concern to reduce the discrepancies between different users, which can be caused by the use of uncommon words or a difficult text.

From this process, it is possible to identify a typing rhythm for each participant, composed of a set of characteristics extracted from the keypresses during the data acquisition process. Such characteristics are known as hold time (H), up time (U) and down-down time (DD). The hold time represents the duration of a keypress; the up time represents the time elapsed between releasing the current key and pressing the next one, and; the down-down time represents the interval between pressing the current key and pressing the next one.

2.1.3 Personality Traits Extraction

The Big Five model is a model designed to represent an individual's personality, having been created in psychology, and is currently an accepted and widely studied model. This personality representation model classifies the personality as composed of five major traits that determine each of the characteristics of being, thinking, and acting of an individual.

The Big Five traits are openness, agreeableness, extraversion, conscientiousness, and neuroticism. These five traits can be divided into six subsets of characteristics, known as facets, to allow a more precise and detailed personality analysis.

A standard way of extracting an individual's personality traits is by applying a questionnaire containing a series of questions to map each personality's specific characteristics. There are different questionnaires based on The Big Five model. One of them is the Neo-International Personality Item Pool (NEO-IPIP), consisting of 300 questions distributed equally among the big five traits. The participant has to choose the answer that best suits him, among the five available alternatives, which vary according to the Likert scale (Likert, 1932), ranging from "totally agree" to "strongly disagree". Due to the number of questions that compose it, the application of NEO-IPIP requires a large amount of time, resulting in inaccurate answers due to the participant's tiredness or even incomplete questionnaires due to participants giving up during the process.

To reduce the amount of time required to apply a self-assessment questionnaire, Gosling, Rentfrow, and Sawnn (Gosling et al., 2003) developed the TIPI, a self-assessment questionnaire derived from NEO-IPIP and composed of only ten questions. Due to its small size, TIPI can not extract Big Five characteristics as accurately as NEO-IPIP does. However, all Big Five traits are mapped. Its application is carried out similarly to NEO-IPIP, where the participant must choose the answer that best suits him from the seven available alternatives, following the 7-point Likert scale, which vary from "totally agree" to "totally disagree".

In this study, the TIPI questionnaire was used as an approach to extract the participants' personalities. It was adapted to be used in the data acquisition web page. The ten questions from the original questionnaire were presented sequentially, with their respective alternatives. The interface has just a "next" button to take the participant to the next question without allowing him to change the previous question's answer.

2.2 Pre-processing

The pre-processing step consists of removing irrelevant data, such as repeated or non-representative information, and performing transformations in the data so that the resulting dataset is better suited for neural network input than the original. We used the pre-processing approach described in (Montalvão Filho and Freire, 2006) to equalize the keystroke data. This approach proved to be advantageous when applied to keystroke data for biometric identification. The equalization function can be described as follows:

$$g(x) = \frac{1}{1 + \exp(-\frac{K(\log_e(x)-\mu_y)}{\sigma_y})}$$

where K is a constant with value 1.7 and x is a time interval. The normalization function maps the values of x to a normal distribution with mean μ_y and standard deviation σ_y, assuming that x follows approximately a distribution log-normal.

2.3 Analysis

With the data obtained in the data acquisition process, artificial neural networks were trained using the keystroke data as input and with information about the personality traits as output. The neural network architectures were composed of an input layer, a hidden layer, and an output layer.

To classify the keystroke data, neural networks with two different output types were trained:

- Output of seven Likert scale values, as obtained with the TIPI questionnaire.
- Output of two values, obtained by the binarization of the results of the TIPI questionnaire. Results with values greater than or equal to 5 were mapped to 1, while results less than 5 were mapped to 0.

Figure 1 represents the structure of the neural network used in the Likert scale approach. Figure 2, on the other hand, represents the structure of the neural network used in the binarized approach.

The two output formats of the neural networks are closely related to the questions Q1 and Q2 proposed in the beginning of this section. The neural networks with output in the Likert scale format aim to identify exactly how much a specific personality trait represents the individual's personality (Q1). It can be directly compared with the result obtained through the

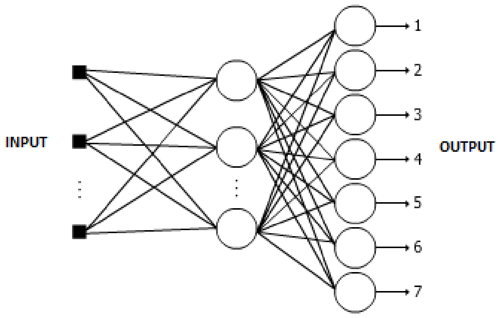

Figure 1: Structure of the neural network used in the Likert scale approach.

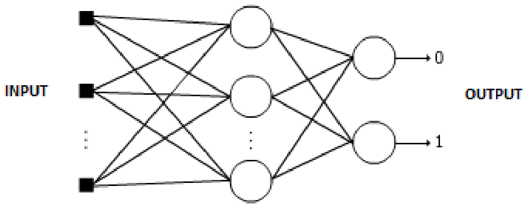

Figure 2: Structure of the neural network used in the binarized approach.

application of the TIPI questionnaire. The neural networks with binary outputs aim to identify whether a personality trait stands out in an individual's personality (Q2). The training and evaluation of this approach were done with the binarized TIPI questionnaire. In both approaches, the neural network output is considered correct when its value is equal to the value of the TIPI questionnaire.

Raw keystroke dynamics data were used as input to the neural networks due to a lack of a formal definition in the literature regarding the relationship of a specific characteristic of the keystroke dynamic, such as the typing speed, with a specific personality trait. Raw data were used as input in order to the neural network define by itself which characteristics are most relevant for each personality trait. As an alternative to the raw keystroke data, the equalized input data, pre-processed as described in Subsection 2.2 was also used.

The acquired keystroke data was used in three different ways as the input of the network: only the hold time data; only the down-down time, and; the combination of hold time and down-down time data simultaneously. During the data acquisition process, 376 time intervals were extracted from the keyboard events, 188 of them referring to hold time and 188 referring to up time. The down-down time intervals were calculated from these two vectors, also composed of 188 time intervals.

Twelve different experiments were done. The experiments are defined by all combinations of three input types, two output types, and the use or not of the equalization method. In each experiment, five neural networks were trained, one for each personality trait, i.e. each trait was analyzed individually by its respective neural network.

The experiments were performed by applying the data to multilayer neural networks with similar architecture but with the number of inputs and outputs varying according to the data being used. The number of neurons in the middle layer is the same as the number of inputs. From the 177 participants in the data acquisition step, 85 were used in the neural network training process, 46 were used for the validation step, and 46 for the testing step.

3 RESULTS

The experiments presented in this work were carried out using the input data selected in the neural network, and comparing them with the expected output for each of the inputs.

3.1 Likert Scale Experiments

The Likert scale (Likert, 1932) is a type of scale where the interviewees must specify their level of agreement with a statement, having been developed specifically for psychometric questionnaires. It can be presented in the format of three, five, or seven points. In this study, seven points were used, that is, each question has seven answer options, as this is the standard adopted in the development of the TIPI questionnaire.

Data equalization was performed following the method described by (Montalvão Filho and Freire, 2006), a method used in biometric analyses aimed at authentication purposes. As it has shown good results, it was decided to use the same approach in order to compare the results obtained by the experiments with and without the application of the equalization method. However, as stated by (Montalvão Filho and Freire, 2006) in their study, equalization approaches in conjunction with neural networks can be considered redundant given that, due to its learning process, the neural networks equalize the input data. The application of the equalization method was carried out using mean (μ) 128.4094 and standard deviation (σ) 842.9373.

Figure 3 shows a comparison of the results obtained in all the experiments carried out following the approach with the Likert scale.

In the literature, the down-down time is considered the characteristic of the typing rhythm that carries the greatest amount of information about the in-

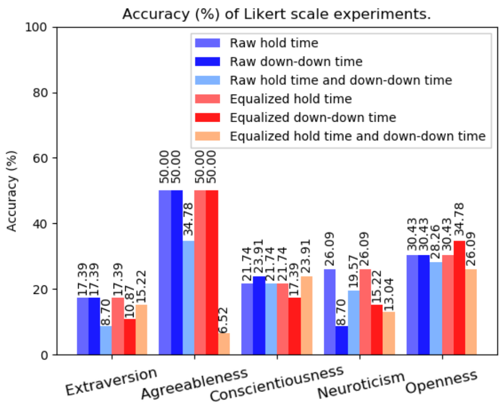

Figure 3: Accuracy (%) of Likert scale experiments.

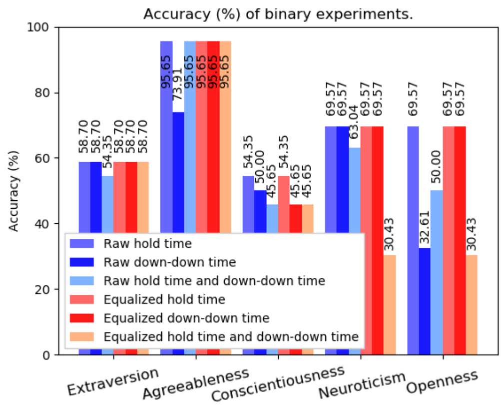

Figure 4: Accuracy (%) of binary experiments.

dividual. For this reason, the down-down time was extracted together with the other characteristics of the typing rhythm (hold time and up time), in order to provide the neural network with as much information as possible with the minimum necessary characteristics. Figure 3 shows a comparison between the equalized approach and the non-equalized approach, using data from the down-down time, where the results obtained varied between 8.70% and 50%.

From the analysis of all the results obtained by the neural network approaches with output on the Likert scale, presented in the Figure 3, it was observed that the success rates varied between 6.52% and 50%, with an average of 24.60% of correct answers, which is unsatisfactory for the prediction of how much a personality trait is present in an individual's personality.

3.2 Binary Experiments

Neural networks with binary outputs were developed to identify which personality traits stand out in an individual's personality. The binary approach allows a clearer identification of which personality traits stand out in a specific individual's personality, thus allowing the network to predict which personality traits are in evidence in a given personality. In this stydy, traits classified with a value greater than or equal to 5, according to the 7-point Likert scale, are considered present (1), and traits with values less than 5 are considered absent (0).

Even with accuracies reaching 95.65%, it cannot be said with certainty that the hold time input with binary scale output approach, shown in Figure 4, is capable of indicating whether the personality traits studied are likely to be mapped through the binary approach, that is, to determine whether or not a personality trait is highlighted in an individual's personality, without first validating the results obtained in conjunction with the analysis of the probability distribution between the classes used in this approach.

Figure 4 shows the accuracies for each of the experiments carried out through the application of the binary approach, with results between 30.43% and 95.65%. With accuracies above 95%, as shown by the personality trait agreeableness in the Figures 4, the binary approaches in general presented accuracies considered high in a preliminary analysis.

However, when compared with the probability distribution of the analyzed classes, presented in Section 3.3, we can conclude that the results obtained are unsatisfactory as it is evident that the same result could be achieved by a classifier guessing the most frequent class. Thus, to verify how significant the results obtained are, it was decided to perform additional tests, presented in Section 3.3.

3.3 Prior Knowledge Analysis

To validate the neural networks' results, we carried out an additional experiment to compare them with an approach using prior knowledge. In the prior knowledge approach, the probability distribution of the analyzed classes is known, as shown in Figure 5 and Figure 6.

This analysis was performed with each of the output types produced by neural networks (Likert scale and binary), in order to identify which of the possible outputs is the most repeated (mode) in the training set of each approach, and then use that answer as the only answer to predict the test set data. Thus, the aim is to prove that the experiments developed using neural networks do not perform better than a purely statistical approach, and these results are not relevant enough to predict an individual's personality traits.

Figure 7 and Figure 8 illustrate the results obtained when comparing these experiments. Figure 7 and Figure 8 show that, although some of the results obtained by neural networks are superior to those of

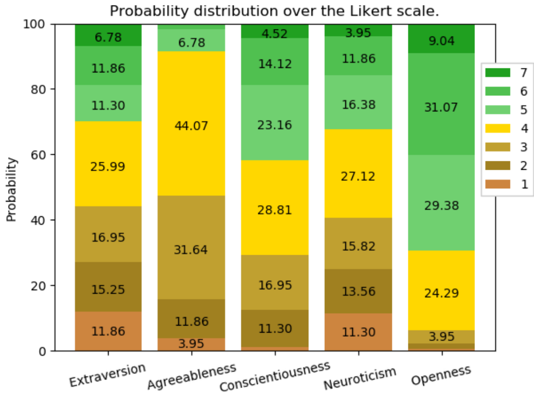

Figure 5: Probability distribution over the Likert scale.

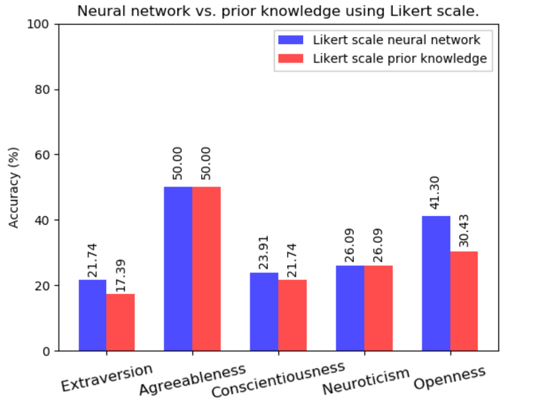

Figure 7: Neural network vs. prior knowledge using Likert scale.

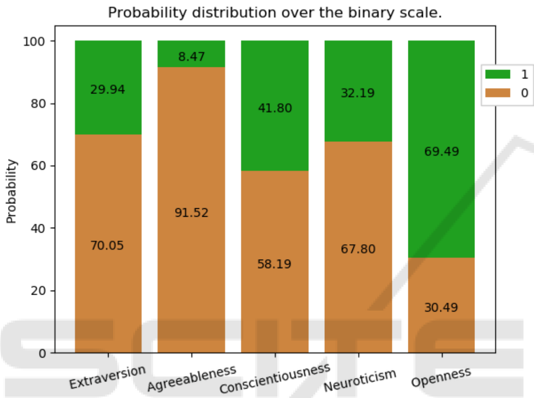

Figure 6: Probability distribution over the binary scale.

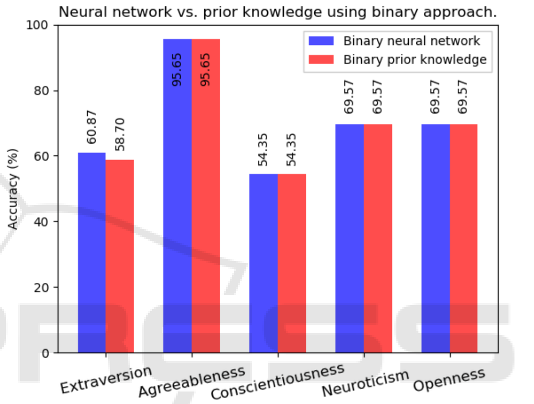

Figure 8: Neural network vs. prior knowledge using binary approach.

analysis with prior knowledge, it is not possible to safely say that neural networks are capable of inferring the personality of an individual.

3.4 Hypothesis Testing

A series of hypothesis tests were done to verify the reliability of the results obtained. One test for each personality trait was done to confirm that the results are unsatisfactory to predict an individual's personality traits through keystroke dynamics characteristics.

Hypothesis testing is a statistical method for analyzing samples through the theory of probabilities. In order to perform a hypothesis test it is necessary to have two hypotheses, known as (i) null hypothesis (H_0); and (ii) alternative hypothesis (H_1). The null hypothesis is the hypothesis that we assume to be true, while the alternative hypothesis is the hypothesis that will be considered true if the null hypothesis is rejected.

In a hypothesis test, two types of errors can occur. Type I error is the rejection of the null hypothesis (H_0) when it is actually true. On the other hand, Type II error is the failure to reject a false null hypothesis (H_0). Our null hypothesis (H_0) states that an approach based on neural networks is as or less effective than choosing the most likely result, while our alternative hypothesis (H_1) states that an approach based on neural networks is more effective than choosing the most likely outcome. The following formula was used to perform the hypothesis tests:

$$z = \frac{a - b}{\frac{\sigma}{\sqrt{n}}} \tag{1}$$

where a represents correct classifications by the neural network, b represents the correct classifications by the approach with prior knowledge, both expressed in the number of people, n represents the size of the test population, and σ represents the population standard deviation.

The hypothesis test was built with a 5% significance level, using the Equation 1, which is a unilateral hypothesis test on the right, in order to prove that the alternative hypothesis (H_1) is true. For a hypothesis test with these characteristics, the critical region regarding the level of significance is represented by

Table 1: hypothesis testing of Likert scale experiments.

Personality trait	Neural network result (a/n)	Average expected output (b/n)	Standard deviation (σ)	Hypothesis testing result (z)
Extraversion	17.39%	17.39%	2.57	0.00
Agreeableness	50.00%	60.87%	3.39	-10.00
Conscientiousness	23.91%	23.91%	2.80	0.00
Neuroticism	26.09%	21.74%	2.98	4.55
Openness	34.78%	34.78%	3.12	0.00

Table 2: Hypothesis testing of binary approach experiments.

Personality trait	Neural network result (a/n)	Average expected output (b/n)	Standard deviation (σ)	Hypothesis testing result (z)
Extraversion	58.70%	58.70%	3.34	0.00
Agreeableness	95.65%	82.61%	1.38	29.48
Conscientiousness	54.35%	54.35%	3.38	0.00
Neuroticism	69.57%	60.87%	3.12	8.69
Openness	69.57%	69.57%	3.12	0.00

$z > 1.64$. Thus, for the alternative hypothesis to be considered true, that is, to reject the null hypothesis, the result obtained through the hypothesis test, represented by z, must be greater than 1.64.

Table 1 shows the hypothesis tests performed with the Likert scale approach, and Table 2 shows the hypothesis tests performed with the binary approach. The tables present the resulting z values obtained through the hypothesis tests performed for each approach. To perform the hypothesis tests, we used the same test set used for evaluating the neural networks, with size $n = 46$. The results shown in the column "neural network result" refer to the best results (highest accuracy) of the approach in detecting the personality trait in question.

Analyzing the result of the hypothesis tests, represented by the column z in the tables 1 and 2, we can see that only three of them obtained a result inside the critical region, i.e., $z > 1.64$. In the other seven tests, the z is outside the critical region, so we do not reject the null hypothesis, which states that neural networks are no better than the a priori approach with a confidence of 95%. The characteristics extracted from the keystroke dynamics probably do not present enough information to map an individual's personality traits. The similarity between the results obtained through an approach based on the choice of the most likely personality trait and an approach based on neural networks is evidenced by the number of tests with z equal to zero.

4 CONCLUSIONS

In this study, 12 different experiments were carried out to search for the relationship between an individual's typing rhythm and his personality traits. A dataset was acquired with the keystroke dynamics data extracted from 177 volunteers and the personality traits of each one. A data acquisition tool was developed specifically for this study and was made available online. The experiments were designed to answer two different questions. Q1: Is it possible to measure how much a given personality trait is present in an individual's personality through the typing rhythm? And Q2: Is it possible to determine which personality traits stand out in the individual's personality through the typing rhythm?

Experiments aimed at answering question Q1 measured the personality traits' intensity in a 7-point Likert scale for each participant. The best neural network classifiers resulted in the following accuracies for each personality trait: extraversion 17.39%; agreeableness 50.00%; conscientiousness 23.91%; neuroticism 26.09%, and; openness 34.78%.

In the experiments aimed at answering question Q2, a binary approach was used. The objective of the experiments was to identify whether or not a personality trait is present in an individual's personality. So, the results in Likert scale were binarized. Values greater or equal to 5 were mapped to 1; otherwise, they were mapped to 0. The binary experiments resulted in higher accuracies than the Likert scale experiments: extraversion 60.87%; agreeableness 95.65%; conscientiousness 54.35%; neuroticism 69.57%, and; openness 69.57%. However, the improvement observed is due to the reduction in the number of classes analyzed from seven to two, resulting in higher accuracies. Even so, the results obtained by this approach are equivalent to those from the approach with prior knowledge.

Finally, when analyzing the results obtained, we concluded that it was not possible to identify an individual's personality traits from the typing rhythm using the approaches described in this work. The exclusive use of keystroke dynamics characteristics may not provide enough information to map the personality traits of an individual.

Even knowing the limitations of a conventional computer keyboard, as a source of information on characteristics capable of differentiating individuals from each other, the usage of the keyboard as an approach is encouraged by Solanki and Shukla (Solanki and Shukla, 2014), Nahin (Nahin et al., 2014) and Kolakowska (Kołakowska et al., 2013). They confirm the benefits of using the typing rhythm from a conventional computer keyboard, which is inexpensive and already widely used in most computer systems, in addition to being a non-intrusive approach and easily adaptable to different computer systems, including smartphones with touchscreens.

Due to the unsatisfactory results on extracting personality traits, we believe that it is not possible to clearly map an individual's personality traits through the keystroke dynamics. On the other hand, we believe in the possibility of success in the development of studies aimed at new approaches and experiments focused on mapping information with a greater relationship with human motor functions, such as emotions and emotional state, as presented by Zimmermann (Zimmermann et al., 2003). Such work can be performed using an adaptation of the data acquisition tool already developed, using the same data acquisition process, adapting only the self-assessment questionnaire to map emotions and emotional states.

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