Optimization of Multimodal Trait Prediction Using Particle Swarm Optimization

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Abstract: Multimodal trait prediction is one of the hardest problems in the domain of Computer Science, Machine Learning, and neural networks. Human traits are subjected to changes in terms of time, situation, place, observer, etc. This paper will try to overcome the problem through the optimization of multimodal trait prediction using Particle Swarm Optimization (PSO) algorithm. Parameter optimization problem based on PSO shown in this paper represents a method that is more efficient for both linear and nonlinear models. The obtained results show that PSO can improve both the prediction of the aggregation model which gives a linear approximation of traits and the nonlinear robust estimation models based on the Huber function.

Keywords: Particle Swarm Optimization, Metaheuristics, Aggregation functions, Robust loss function, Apparent personality analysis, Personality classification.

1. Introduction

Automatic apparent trait analysis and trait prediction use modern computer methods to predict human personality from various input parameters such as text, handwriting, image, and audio supports. The main aim of the models used in computer science is not to understand traits, but to predict them. In last two decades, psychology and other disciplines like computer science, economy, business, education, and also health-care tried to better understand human traits (John, Robins & Pervin, 2010). The most popular approaches for detecting human traits in psychology are the Eysenck personality questionnaire-revised (Eysenck et al., 1985) or so-called "three-factor model" and Big Five personality trait model (McCrae & Costa, 1987) or the so-called "five-factor model". The computer science field, especially subfields like Machine Learning and Artificial Intelligence, made big progress in the detection of human traits from visual and audio modalities (Zhang & Zhang, 2016), video recordings (Ponce-López et al., 2016) and handwriting (Gavrilescu & Vizireanu, 2018). The Big Five, also called OCEAN (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) model is a very promising model for detecting human traits. These traits can also be arranged into facets, which are better representative of human traits; they are introduced by Paul Costa and Robert McCrae in the NEO-Personality Inventory (NEO-PI) manual which is mostly used for detecting human traits (McCrae & Costa, 2003). In 1992 the same authors proposed NEO-PI-R the Revised NEO Personality Inventory model (Costa & McCrae, 1992). NEO-PI-R represents personality inventory models that represent Big Five traits and it can also be used to represent facets.

Automatic personality trait prediction from text, handwriting, image, and audio supports represents a multimodal approach mainly based on building classifiers using supervised or unsupervised Machine Learning which tries to learn from data patterns. This way of approaching the problem gives good and viable results, and even overcomes some of the problems which are present in the accurate personality judgment (Funder, 2012), like the problem of the observer (the situation in which the subject is observing or is observed). The paper was also introduced by Leigh Wilks (Wilks, 2009) who demonstrated that traits are very stable over time and that if changes occur, they are minimal or can be predicted.

Approaches which use aggregation models (Vukojičić & Veinović, 2021a) that give one representative value of personality traits out of multimodal trait prediction from text, handwriting, image, and audio supports show that trait prediction can be slightly improved. The main problem of the model shown in paper (Vukojičić & Veinović, 2021a) is that the model creates outliers by using linear aggregation functions (Min, Max) for a final trait candidate. To overcome this problem, a nonlinear function can be used after aggregation, for improving the model (Vukojičić & Veinović, 2021b) and for a better trait extraction overall.

This paper presents a model based on swarm intelligence which uses Particle Swarm Optimization (PSO) algorithm (Kennedy &

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Eberhart, 1995; Poli, Kennedy & Blackwell, 2007). PSO is utilized to improve the optimization of a nonlinear function and get better results in the apparent personality trait detection. In the following, this method is referred to as Soft Aggregation Model (SAM).

Figure 1 illustrates the model proposed in this paper. It is based on various methods for the trait extraction part. Then, the model is based on the aggregation layer which consists in Min, Max, Median and Mean aggregation functions. The output of the aggregation layer represents the input of the fit function with the sum of the Huber penalty function for each component. Next, the result of the fit function is optimized using a Particle Swarm Optimization algorithm which gives, at the output, one value for each of the OCEAN traits (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism). The optimization of the Soft Aggregation Model can give more realistic results, when the model is accomplished.

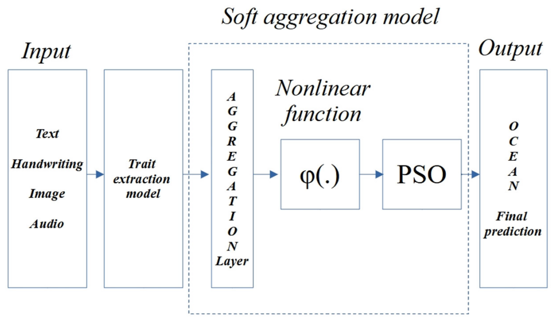


Figure 1. The framework of the proposed model with aggregation layer, nonlinear function, and particle swarm optimization, soft aggregation model

The rest of this paper is organized as follows: Section 2 synthesizes some data from the specialized literature. Section 3 introduces the proposed method with Particle Swarm Optimization and database review and Section 4 presents the proposed experiment. Section 5 provides discussions regarding the results of the experiment, while Section 6 offers the conclusion of the study and some prospects for the development of the proposed research.

2. Literature Review

Differentiating individualities, explaining why each person has different traits and understanding why their traits are different represent a wide research area in the psychology domain. Models like Big Five try to explain the traits of individuals based on five factors: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Openness tries to predict how artistic or imaginative a person is, while conscientiousness tries to explain how organized or responsible a person is. Extraversion tries to predict how active or energetic a person is, while agreeableness strives to detect how friendly or cooperative an individual is. Finally, neuroticism strives to detect emotional characteristics of individuals, especially the emotional instability (Alam & Riccardi, 2014).

Automatic detection of traits using supervised and unsupervised models of computing is a new movement in the field of computer science. These methods are trying to overcome many problems that observers and subjects can have during trait detection. Most of the models are based on text, handwriting, image, and audio inputs. OCEAN characteristics detected for textual outputs are giving the solid output (Majumder et al., 2017; Mikolov et al., 2013). This way of predicting traits is very limited because pure text cannot give many characteristics of individuals. Methods based on handwriting are better as they provide more accurate results (Fallah & Khotanlou, 2016), being one of the oldest methods for detecting human traits. Audio input and image input give good results, somewhere between the text and handwriting, in terms of accuracy, sometimes even better than those two, but, at the same time, it is very hard to process audio and visual characteristics, because of the noise (Zhang et al., 2016; Davis & Mermelstein, 1980; Costa & McCrae, 2008). There are also models that can predict traits from just one image of the subject.

The problem with the individual methods of trait extraction from different inputs is that a bigger picture of the OCEAN characteristics cannot be obtained. Some traits are better predicted from handwriting like neuroticism and openness to experience while some traits like agreeableness can be better predicted from the image and voice. To overcome this problem papers like (Vukojičić & Veinović, 2021a) are using aggregation functions at the end of the model to get a better prediction. The problem with this approach is that aggregation layers based on the linear models like Min, Max are creating too many outliers. This can be solved with nonlinearity, namely using a nonlinear function at the end of the aggregation can be the best fit for the aggregation values (Vukojičić & Veinović, 2021b). Functions like Huber penalty function are giving even better results than simple linear aggregation functions. The problem with this method is that rigid results are obtained. The present paper tries to overcome this problem by introducing the Soft Aggregation Model (SAM) method which uses Particle Swarm Optimization (PSO) after nonlinear function to get even better results for the end trait prediction.

2.1 Extraction Models Before SAM

Multimodal trait prediction is often related to several input parameters like images, sounds, audio, and video parameters which are combined into a single discrete output. This output will represent each one of OCEAN/Big-5 characteristics.

One of the oldest methods of personal trait extraction is based on a handwriting. The idea of extracting traits from handwriting of individuals represents one of the hardest methods of trait prediction and human personality trait analysis. Models based on handwriting often use patterns that can occur in the handwriting of individuals. Extraction methods based on writing and Machine Learning methods (Chen & Lin, 2017) showed that the result of the prediction from the handwriting can lead to an accuracy of 62.5% to 83.9%.

The results also indicate that traits extracted from handwriting are stable over time. Handwriting can also include indicators for happiness, excitement, different emotional states, anger, and calm. The work in this area is based on neural networks which, in their turn, are based on the Hidden Markov Models (Fallah & Khotanlou, 2016) where the Hidden Markov Model is used for classification of the individual traits. The result obtained by using the Hidden Markov Model and neural networks can lead to an accuracy of 72%.

The trait prediction method based on personality trait extraction from the text is very popular in the trait extraction literature, because of the expansions of social media and other forms of digital communication. The term "text" needs to be redefined as digital data, as it can be in the form of a typed short sentence, tweet, post, essay, or longer written content. In the domain of personality trait detection and extraction, there are some popular models based on word vectorization (Mikolov et al., 2013) and convolutional neural networks in combination with Mairesse features (Majumder et al., 2017). The results of these mentioned works led to an accuracy of 56% to 62%.

Personality trait extraction based on audio inputs consists in two categories: feature and frequency. Here the models are based on Mel Frequency Cepstral Coefficients (MFCC) and Linear Prediction Cepstral Coefficient (LPCC) (Gilpin et al., 2018; Davis & Mermelstein, 1980). The accuracy of these models is around 70%, the main problem with trait detection and extraction from the audio signal being the quality of the signal and the noise presented in the signal itself.

Modern network can combine audio and visual cues and also the surroundings cues of the subject, based on the deep convolutional neural networks, with Local Gabor Binary Patterns provided by the Three Orthogonal Planes video descriptor, which is an openSMILE acoustic features extractor (Gürpinar et al., 2016).

Main research on models based on images, video materials and other visual supports is mostly based on YouTube and Facebook and other video sharing platforms, on which authors are doing multimodal sentiment analysis, with the usage of deep learning, Gated Multimodal Embedding LSTM with Temporal Attention (GME-LSTM(A)) (Chen & Lin, 2017). Other approaches based on images make use of convolutional neural networks (Krizhevsky et al., 2012) with an error rate of 37% to 17% and a neural network of 650.000 neurons. Then, they were followed by the design of a network: five convolutional layers, a max-pooling layer, three fully-connected layers, a softmax layer, and the output. Other approaches used Deep Bimodal Regression (DBR) framework, with the convolutional neural network for visual cues (Zhang et al., 2016) combined with the linear regression for audio cues.

3. The Proposed Soft Aggregation Model

The proposed method will be based on the Soft Aggregation Model shown in Figure 1. The model is constructed from three different parts. The first part of the model is based on the Min, Max, Mean and Median aggregation functions. The second part of the model is based on the Huber function employed to minimize the outliers, and the third part of the model is represented by Particle Swarm Optimization algorithm used on nonlinear function.

The PSO algorithm will help to achieve some form of simulation of social behaviour and represents a more natural way of extracting personal traits. Previous work was based on the linear aggregation function and nonlinear functions like the Huber function. The problem with "hard" approaches is that there is a possibility of obtaining rigid values for personal traits. In order to have a more natural and flexible approach swarm intelligence algorithm will be used. This will provide a more natural performance and a less rigid approach.

If PSO is used in a linear space, on aggregation functions like Min, Max, Mean, and Median, the problem is that Min and Max affect the results and, in its turn, the proposed PSO algorithm will also be affected by these outliers. It can be said that the bad terms existing from the beginning will result in bad PSO prediction. In order to improve this situation, Huber nonlinear function is used, which makes the system less sensitive to outliers. By improving the terms for the PSO algorithm, the final results will also be improved.

3.1 Aggregation Model

The aggregation model is based on the paper of Vukojičić & Veinović (2021a). This model is built on several aggregation functions (Min, Max, Mean, Median (Grabisch et al., 2009)). The output of the previous models based on text, image, handwriting, and audio supports can be shown as a unique value obtained when an aggregation function is used on the output of the trait extraction model. Here, the goal is to improve the multimodal trait extraction from several inputs. The Min and Max aggregation functions can be defined as functions that operate on the array of inputs and extract the smallest element, in the case of the Min aggregation function, and the biggest element, in the case of the Max aggregation function. Mean and Median aggregation functions (see equations (1) and (2)) can be defined as:

$$mean(x) = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

$$median(x) = \frac{x_{n_A} + x_{n_B}}{2} \tag{2}$$

Mean aggregation function is defined as the sum of all the elements present in the output of the trait extraction model. Then, this number needs to be divided by the number of elements. In the present case, n represents the number of elements which is 4. For the Median aggregation function, $n = 4$, $n_A = \frac{n}{2}$, and $n_B = \frac{n}{2} + 1$, where the second number present in the output of the trait extraction model can be represented as n_A and the third number present in the output of the trait extraction model can be represented as n_B.

The main problem with this approach is that Min and Max aggregation models are creating outliers. Mean and Median aggregation functions can give a better prediction than Min and Max aggregation functions. But, in order to improve the method, another layer needs to be introduced in the proposed model, which is based on the robust estimation and Huber function used to achieve a more natural way of trait prediction.

3.2 Robust Estimation

Outliers generated from Min and Max layers provide bad predictions, but, in some cases, some traits are better predicted when using Max aggregation function than when using Mean and Median aggregation functions. This means that, in the final prediction, all the aggregation models need to be used in order to achieve more realistic results. To overcome this problem, a new layer will be introduced (Vukojičić & Veinović, 2021b) based on the Huber loss function (Huber, 1992) which is part of the robust regression. The introduction of the Huber function at the center of the model will lead to better prediction and the present model will be less sensitive to the outliers created by Min and Max aggregation functions.

Huber loss function (see equation (3)) will be defined as:

$$L_\delta(a) = \begin{cases} \frac{1}{2}a^2 & for\,|a| \le \delta \\ \delta(|a| - \frac{1}{2}\delta), & otherwise \end{cases} \tag{3}$$

Values of a will change the function from linear for large values and quadratic for small values of a. The value of δ that leads to the best results will be 1.35. Setting its value to $\delta > 3$ will lead to Mean Squared Error, while setting its value to $\delta < 1.3$ will lead to Mean Absolute Error (Kovačević et al., 2017). The output of the aggregation function needs to be sorted from the smallest to the largest output for all five traits (O, C, E, A, N).

Robust estimation and Huber function can lead to better results in comparison with Min and Max aggregation models which produce outliers. Sometimes, models like Median and Mean aggregation functions can produce better results in comparison with the Huber function, while sometimes can produce even worse results than Huber function. Huber function will also introduce more natural prediction of the models. The output that is created with the Huber function can be improved by using the Particle Swarm Optimization (PSO) algorithm which will be presented in the next subsection.

3.3 Particle Swarm Optimization (PSO)

The method used for the final layer is based on the division of labor swarm algorithm. The chosen algorithm is Particle Swarm Optimization (PSO), proposed by Kennedy & Eberhart (1995). The purpose of this algorithm is to use multiple agents called particles (namely, *n* particles), to simulate the behavior of fuzzy objects. This algorithm is based on the simulation of the behavior of a flock of birds or a shoal of fish. Swarm algorithms are getting a lot of attention among the researchers because of their performance and ease of implementation (Subotic & Tuba, 2014; Bacanin & Tuba, 2012) and a lot of them are used for modification of the already existing algorithms and models based on Artificial Intelligence (Tuba et al., 2022).

Vector x_i will be used as both a solution vector, and a position of the particle. The overall motion of the particle will be represented by velocity v_i. The position of the particle and the velocity of the particle can be updated with each iteration and pseudotime t (4,5).

$$v_i^{t+1} = v_i^t + \alpha \in_1 [g^* - x_i^t] + \beta \in_2 [x_i^* - x_i^t], \tag{4}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \Delta t. \tag{5}$$

From equations (4) and (5), $\in_1$ and $\in_2$ can be defined as two random numbers with uniform distribution, situated within the range [0, 1]. Time Δt represented in the equation is the discrete-time and it can be set to $\Delta t = 1$, g^* represents the best solution of the entire population, at each iteration t, while x_i^* represents the best individual solution for particle i, which will be represented for the entire search history, up to iteration t (Yang, 2020). Parameters α, β represent the learning parameters in the equation and are defined within the range [0, 2] (Bansal, Singh & Pal, 2019). By changing the learning parameters, the stability of the proposed swarm algorithm can get better or worsen.

In the pseudocode of the algorithm (see Algorithm 1), *D*-dimensional search space is initialized and *S* represents the swarm size:

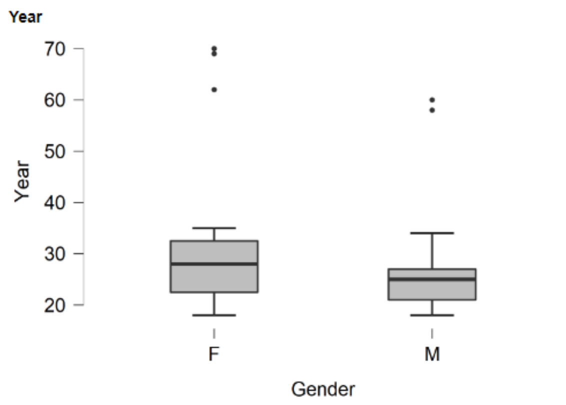
Algorithm 1. Particle Swarm Optimization (PSO) algorithm (Bansal, Singh & Pal, 2019)

```
for t=1 to the maximum number of iterations do
  for i=1 to S do
    for d=1 to D do
      Use velocity update equation (4);
      Use position update equation (5);
    end
    Computer fitness of update position;
    If needed, update historical information for pbest and gbest;
  end
  Terminate if gbest meets problem requirements;
end
```

Every particle will learn from other particles, which is called social learning, and from its own experience, which is called cognitive learning. From social learning, it can be seen that every particle stores the best solution visited by all the particles and this is called *gbest*. The best solution for the particle itself is called *pbest*. PSO algorithm will be applied to the nonlinear Huber function and the best discrete value that represents the entire function and, in the present case, the subjects' trait, will be found.

4. Experimental Design

The experiment done in this paper is based on 64 subjects, 33 males and 31 females, aged between 18 and 70. The selected subjects have different education levels, job titles, and origins. The distribution of the subjects' ages and gender is represented in Figure 2. More detailed description of the databased can be seen in papers (Vukojičić & Veinović, 2021a) and (Vukojičić & Veinović, 2021b). The experiment is conducted on the dataset which has output values of the models that extract OCEAN characteristics (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) from inputs (text, handwriting, image or sequences of images, audio supports). All the values will be situated within 0 and 1, for all of the human traits combined with all the model inputs.



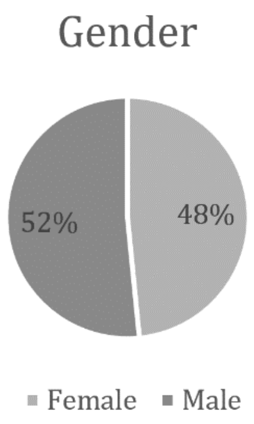


Figure 2. Age and gender distribution of male and female subjects

Here, the goal is to compare the results of the NEO-PI-R test taken by the subjects with the results of the model proposed in this paper. All the subjects provide some textual and handwritten components as well as images (sequences of images) and audio data as input. The output of the trait extraction model, which was shown in Figure 1, is created from this input. Then, the output of the trait extraction model is used as the input of the present proposed Soft Aggregation Model. The output of the Soft Aggregation Model needs to provide a value between 0 and 1 as a final prediction of the subjects' traits for each of the traits (O, C, E, A, N). Particle Swarm Optimization parameters are highly dependent on the problem itself. The parameters that can be chosen are the number of iterations and the swarm size population. In the present experiment, the value of the swarm size is situated between 4 and 900, and the value of several iteration parameters is situated between 10 and 900.

From Figure 4 and Figure 5, it can be seen that the error will not decrease with the increment of the swarm size or of the number of iterations. If too big parameters are used for swarm size or for the number of iterations, it will lead to overfitting and to false predictions of the PSO algorithm. From Figures 4 and 5 it can also be seen that, for this problem, the optimal swarm size is 4 and the optimal number of iterations is 10. Also, the value of swarm size and of the number of iterations will affect the speed of the proposed system. If the value of the swarm size or the value of the number of iterations is increased, the speed of the algorithm is affected, as seen in Figure 5. In order to get the best results from the algorithm, to minimize both the overfitting and the time of the algorithm, the value of the swarm size is chosen as 4 and the value of the number of iterations is chosen as 10.

The relation between the swarm size and several iterations can be seen in Table 1.

Table 1. Attempts related to the swarm size and the number of iterations of the PSO algorithm

Attempts	Swarm size	Number of iterations
1	4	10
2	5	20
3	4	25
4	25	50
5	40	80
6	100	100
7	200	200
8	300	300
9	400	400
10	500	500
11	600	600
12	700	700
13	800	800
14	900	900

5. Results and Discussion

The results presented in this paper include the results that the subjects obtained at NEO-PI-R test, the results of Min, Max and Huber function, and the results of the proposed Soft Aggregation Model. Figure 3 illustrates the results of the Huber function. This approach can lead to a good prediction of personal traits, but it can be improved with the proposed Soft Aggregation Model.

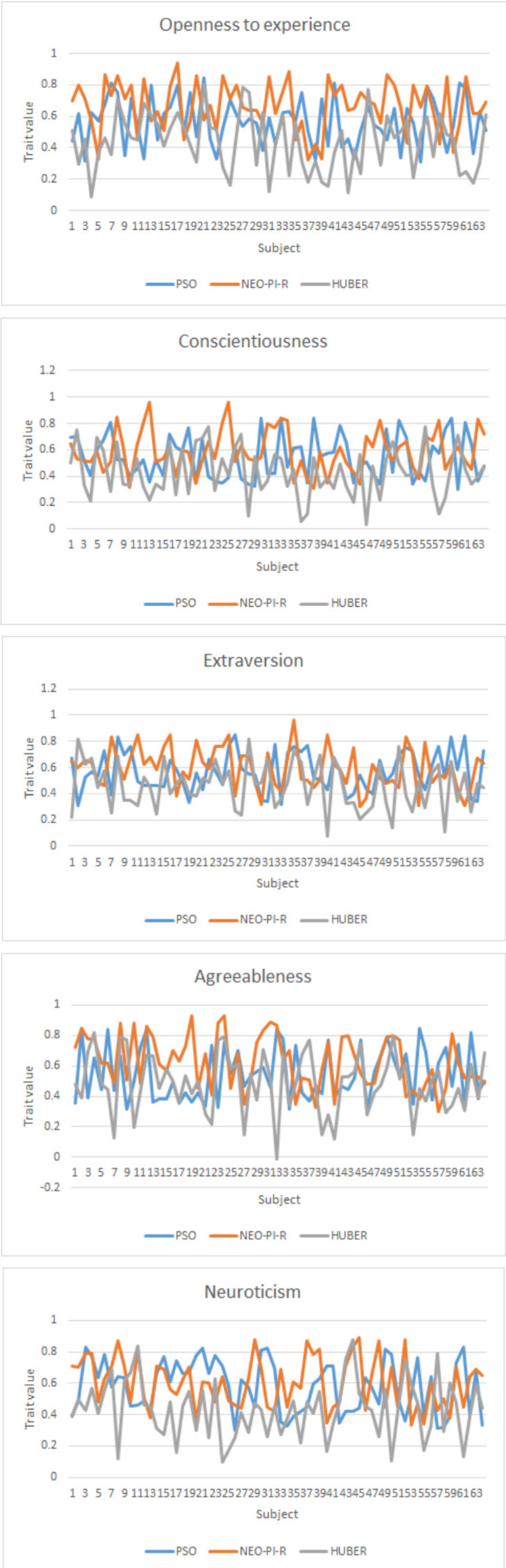


Figure 3. Results of SAM model compared with results of Huber aggregation function and of NEO-PI-R

Particle Swarm Optimization (PSO) algorithm can be used with different iteration parameters and different swarm size parameters shown in Section 4 of this paper. To get better results, different values are used for these parameters. The performance of the algorithm when increasing the swarm size and the number of iterations can be seen in Figures 4 and 5.

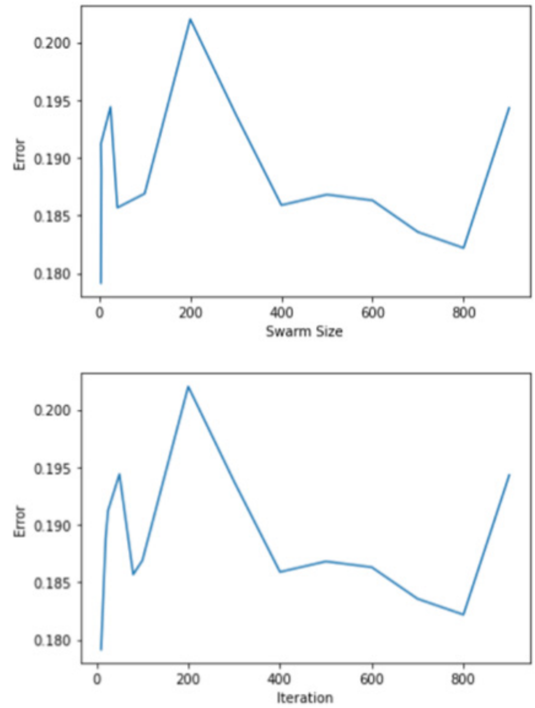


Figure 4. Algorithm performance over different swarm sizes and different numbers of iteration

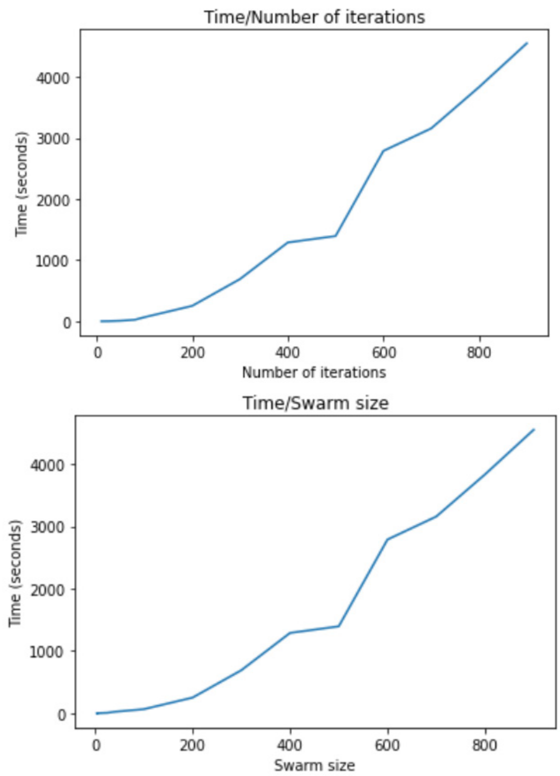


Figure 5. PSO complexity analysis

The results seen in Figures 4 and 5 can be very helpful when deciding what parameters should be used for the proposed PSO algorithm. It can be noticed that the optimal value of the swarm size is between 4 and 25 and of the several iteration parameters is between 10 and 25 (Bansal, Singh & Pal, 2019). It can also be noticed that the value of 700 and 800 of the swarm size and the value of the number of iterations of 700 and 800 can give pretty good results, but they outperform with a small number of iterations and a small swarm size.

If the number of iterations and the swarm sizes are increased, the complexity of the system is also increased. This complexity cannot be justified by a better performance of the entire system.

The comparison regarding the results of absolute and relative error of the previous models based on Huber function and on aggregation functions are shown in Table 2 and Table 3, respectively. It can be seen that the models based on Huber function can achieve a better performance than those based on Min and Max aggregation functions. It can also be seen that the models based on the Particle Swarm Optimization algorithm can achieve even better results and improve the results of models based on Huber function.

In Table 2 and Table 3, the results of PSO are introduced with the next parameters: 4 for the swarm size and 10 for the number of iterations.

Table 2. The comparison between the absolute error results of the proposed Soft Aggregation Model based on PSO and the absolute error results of the models based on Max, Min and Huber functions

	ABSOLUTE ERROR [ΔX]				
	O	C	E	A	N
MAX	0.27	0.29	0.35	0.32	0.34
MIN	0.55	0.46	0.46	0.45	0.48
HUBER	0.17	0.16	0.13	0.14	0.14
SAM	**0.11**	**0.14**	**0.10**	**0.14**	**0.13**

Table 3. The comparison between the relative error results of the proposed Soft Aggregation Model based on PSO and the relative error results of the models based on Max, Min and Huber functions

	RELATIVE ERROR[ΔX]				
	O	C	E	A	N
MAX	81%	79%	75%	71%	77%
MIN	52%	60%	72%	63%	68%
HUBER	24%	28%	25%	24%	23%
SAM	18%	20%	22%	18%	19%

6. Conclusion and Future Development

Apparent personality analysis represents one of the hardest problems that can be found in the domain of psychology and Computer Science. NEO-PI-R test can give a very good representation of human traits. This paper proposes a novel approach for the trait extraction model which is called Soft Aggregation Model. This model is based on metaheuristics and Particle Swarm Optimization. The results of the proposed method were tested and compared with the results of the previous papers based on the linear and nonlinear models. This paper shows that the Soft Aggregation Model based on swarm intelligence gives better results for both the linear and nonlinear models based on Huber and aggregation functions. Application of trait extraction and prediction models can be seen in psychological assessment, school environment, human resource field and in many more applications of the real world.

Another thing that should be observed in the field of Personal Computing and automated human trait detection is the ethical side of human trait detection. Because all of the Machine Learning models are appropriate for trait extraction, as the data on which they are operated, the main problem will be how well the data of the model proposed in this paper can be labelled. Human trait can be very hard to label, so it needs to be done mostly by the experts from the field of psychology and with relevant personality test (NEO-PI-R tests). This is an important aspect, because, if data is not labelled very well, the final result of the models (OCEAN characteristics) can be misinterpreted (Mehta et al., 2020).

Future work will be based on a mixture of expert methods (Yuksel et al., 2012) that will be the basis on which the power of Machine Learning should be used to train the neural networks in order to obtain a better prediction of the models and to establish which model can be seen as an expert in the field of trait extraction.

REFERENCES

Alam, F. & Riccardi, G. (2014). Predicting personality traits using multimodal information. In Proceedings of the 2014 ACM Multimedia on Workshop on Computational Personality Recognition (pp. 15-18).

Bacanin, N. & Tuba, M. (2012). Artificial Bee Colony (ABC) Algorithm for Constrained Optimization Improved with Genetic Operators, Studies in Informatics and Control, 21(2), 137-146. DOI: 10.24846/v21i2y201203

Bansal, J. C., Singh, P. K. & Pal, N. R. (Eds.). (2019). Evolutionary and Swarm Intelligence Algorithms, 1-9. Berlin, Germany: Springer.

Chen, Z. & Lin, T. (2017). Automatic personality identification using writing behaviours: an exploratory study, Behaviour & Information Technology, 36(8), 839-845.

Costa, P. T. & McCrae, R. R. (1992). Revised NEO Personality Inventory (NEO-PI-R) and NEO Five-Factor Inventory (NEO-FFI) professional manual. Odessa, FL: Psychological Assessment Resources.

Costa, P. T. & McCrae, R. R. (2008). The Revised NEO Personality Inventory (NEO-PI-R). Sage Publications, Inc.

Davis, S. & Mermelstein, P. (1980). Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences, IEEE Transactions on Acoustics, Speech, And Signal Processing, 28(4), 357-366.

Eysenck, S. B., Eysenck, H. J., & Barrett, P. (1985). A revised version of the psychoticism scale, Personality and Individual Differences, 6(1), 21-29.

Fallah, B. & Khotanlou, H. (2016). Identify human personality parameters based on handwriting using neural network. In Proceedings of the 2016 Artificial Intelligence and Robotics Conference (IRANOPEN), (pp. 120-126). IEEE.

Funder, D. C. (2012). Accurate personality judgment, Current Directions in Psychological Science, 21(3), 177-182.

Gavrilescu, M. & Vizireanu, N. (2018). Predicting the Big Five personality traits from handwriting, EURASIP Journal on Image and Video Processing, 2018(1), 1-17.

Gilpin, L. H., Olson, D. M. & Alrashed, T. (2018). Perception of speaker personality traits using speech signals. In Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1-6).

Grabisch, M., Marichal, J. L., Mesiar, R. & Pap, E. (2009). Aggregation Functions. Series: Encyclopedia of Mathematics and its Applications (No. 127). Cambridge University Press.

Gürpinar, F., Kaya, H. & Salah, A. A. (2016, December). Multimodal fusion of audio, scene, and face features for first impression estimation. In 2016 23rd International Conference on Pattern Recognition (ICPR), (pp. 43-48). IEEE.

Huber, P. J. (1992). Robust estimation of a location parameter. In Kotz, S. & Johnson, N. L. (Eds.), Breakthroughs in Statistics, 492-518. New York, NY: Springer.

John, O. P., Robins, R. W. & Pervin, L. A. (Eds.). (2010). Handbook of Personality: Theory and Research. Guilford Press.

Kennedy, J. & Eberhart, R. (1995). Particle swarm optimization. In Proceedings of ICNN'95 – International Conference on Neural Networks, Vol. 4 (pp. 1942-1948). IEEE.

Kovačević, B., Milosavljevic, M. M., Veinovic, M. & Marković, M. (2017). Robust Digital Processing of Speech Signals. Springer.

Krizhevsky, A., Sutskever, I. & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks, Advances in Neural Information Processing Systems, 25, 1097-1105.

Majumder, N., Poria, S., Gelbukh, A. & Cambria, E. (2017). Deep learning-based document modeling for personality detection from text, IEEE Intelligent Systems, 32(2), 74-79.

McCrae, R. R. & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers, Journal of Personality and Social Psychology, 52(1), 81-90.

McCrae, R. R. & Costa, P. T. (2003). Personality in Adulthood: A Five-Factor Theory Perspective. Guilford Press.

Mehta, Y., Majumder, N., Gelbukh, A. & Cambria, E. (2020). Recent trends in deep learning based personality detection, Artificial Intelligence Review, 53(4), 2313-2339.

Mikolov, T., Yih, W. T. & Zweig, G. (2013). Linguistic regularities in continuous space word representations. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (pp. 746-751).

Poli, R., Kennedy, J. & Blackwell, T. (2007). Particle swarm optimization, Swarm Intelligence, 1(1), 33-57.

Ponce-López, V., Chen, B., Oliu, M., Corneanu, C., Clapés, A., Guyon, I., Baró, X., Escalante, H. J. & Escalera, S. (2016). ChaLearn LAP 2016: First round challenge on first impressions-dataset and results. In European Conference on Computer Vision ECCV 2016 (pp. 400-418). Springer, Cham.

Subotic, M. & Tuba, M. (2014). Parallelized Multiple Swarm Artificial Bee Colony Algorithm (MS-ABC) for Global Optimization, Studies in Informatics and Control, 23(1), 117-126. DOI: 10.24846/v23i1y201412

Tuba, I., Veinovic, M., Tuba, E., Hrosik, R. C. & Tuba, M. (2022). Tuning Convolutional Neural Network Hyperparameters by Bare Bones Fireworks Algorithm, Studies in Informatics and Control, 31(1), 25-35. DOI: 10.24846/v31i1y202203

Vukojičić, M. & Veinović, M. (2021a). Apparent personality analysis based on aggregation model. In Sinteza 2021 - International Scientific Conference on Information Technology and Data Related Research, Belgrad, Serbia (pp. 220-225). DOI: 10.15308/Sinteza-2021-220-225

Vukojičić, M. & Veinović, M. (2021b). Apparent personality analysis based on robust estimation. In Proceedings of the 5th International Conference on Applied Informatics (ICDD), Sibiu, Romania (pp. 145-154).

Wilks, L. (2009). The stability of personality over time as a function of personality trait dominance, Griffith University Undergraduate Psychology Journal, 1, 1-9.

Yang, X. S. (Ed.). (2020). Nature-Inspired Computation and Swarm Intelligence: Algorithms, Theory and Applications. Academic Press.

Yuksel, S. E., Wilson, J. N. & Gader, P. D. (2012). Twenty years of mixture of experts, IEEE Transactions on Neural Networks and Learning Systems, 23(8), 1177-1193.

Zhang, C. L., Zhang, H., Wei, X. S. & Wu, J. (2016). Deep bimodal regression for apparent personality analysis. In European Conference on Computer Vision (pp. 311-324). Springer, Cham.