IJIO
(*International Journal of Industrial Optimization*)
ISSN 2723-3022 (online) | 2714-6006 (printed)
VOL 3, No. 2, 110-120
https://doi.org/10.12928/ijio.v3i2.6242

Graphology analysis for detecting hexaco personality and character through handwriting images by using convolutional neural networks and particle swarm optimization methods

Alvin Barata, Habibullah Akbar*, Marzuki Pilliang, and Anwar Nasihin
Faculty of Computer Science, Esa Unggul University, Jakarta, Indonesia
*Corresponding Author: habibullah.akbar@esaunggul.ac.id

ARTICLE INFO

Article history
Received: June 30, 2022
Revised: August 18, 2022
Accepted: August 28, 2022

Keywords
Convolutional Neural Network;
Particle Swarm Optimization;
Handwriting;
Personality and Character;
Machine Learning Classification;

0

ABSTRACT

Graphology or handwriting analysis can be used to infer the traits of the writers by examining each stroke, space, pressure, and pattern of the handwriting. In this study, we infer a six-dimensional model of human personality (HEXACO) using a Convolutional Neural Network supported by Particle Swarm Optimization. These personalities include Honesty-Humility, Emotionality, eXtraversion, Agreeableness (versus Anger), Conscientiousness, and Openness to Experience. A digital handwriting sample data of 293 different individuals associated with 36 types of personalities were collected and derived from the HEXACO space. A convolutional neural network model called GraphoNet is built and optimized using Particle Swarm Optimization (PSO). The PSO is used to optimize epoch, minibatch, and droupout parameters on the GraphoNet. Although predicting 32 personalities is quite challenging, the GraphoNet predicts personalities with 71.88% accuracy using epoch 100, minibatch 30 and dropout 52% while standard AlexNet only achieves 25%. Moreover, GraphoNet can work with lower resolution (32 x 32 pixels) compared to standard AlexNet (227 x 227 pixels).

INTRODUCTION

There are many methods to communicate which exist through centuries. Communication has been a part of humans' life where it conveys information that runs systems in societies around the globe. One of many methods of communication is handwriting [1]. Handwriting is one of the oldest methods of communication between humans. Recent studies have revealed its relationship to psychological and brain aspects. Specifically, the psychological study of handwriting provides a window into personality structure and is called graphology [1]. Commonly, the structure includes psychological traits, states, temperament, and behaviour. Traditionally, personality reading is done by expert called as graphologists that can relate personality based on handwriting [3]. This is possible since a standard or a set of predefined features such as strokes, curves, shapes, styles, and sizes can be used to identify the personality of the hand writers [2], [3]. However, the analysis of handwriting by graphologists tends to be time-consuming and costly. Moreover, a human graphologist is subjective and has different skills and experiences. Alternatively, computerized analysis has emerged due to progress in artificial intelligence and machine learning methods. Over the past decade studies of automated handwriting analysis have burgeoned [4]–[10].

There is no widely-accepted standard for predicting personality based on handwriting. A study of personality detection and classification by Chitlangia and Malatangi defines five personality traits namely Extrovert, Energetic, Introvert, Optimistic, and Sloppy [11]. They use the Support Vector Machine (SVM) model that extrat image features from handwriting images based on the Histogram of Oriented Gradient. They achieve 80% accuracy with a very limited dataset, only 10 samples per class. However, their personality classification is misleading and has no clear theoretical basis.

Most studies for automated handwriting analysis for personality classification are concentrated on the Five Factor Model (FMM). Gravilescu and Vizirenau used Big Five or Five Factor Model to analyze and detect personality from handwriting images [4]. They proposed a three convolutional neural network consisting of a base layer, handwriting map layer, and top layer for personality classification from handwriting. They have been able to embed traditional-wise methods such as noise reduction, raw segmentation, and handwriting feature extraction within the network. Their results attain decent accuracy performance as follows. The Openness to Experience, Neuroticism, and Extraversion attain accuracy over than 84%. On the other hand, the Conscientiousness dan Agreeableness attain accuracy around 77%. The dataset that was used for the research was 128 that was divided equally for male and female handwriting samples. However, they have not compared their method with state-of-the-art.

Another study on the FFM model is conducted by [12]. They present a set of convolutional neural networks called Personality Analyzing Network. One model for personality traits, N, E, and O, and the other models for trait A and trait C respectively. The strength of the study is due to comparison with traditional methods such as Support Vector Machine and Decision Tree. The data used are taken from many respondents collected using an offline questionnaire. The results showed that their method (the average accuracy is 76%) performs better than other models. The lower performances from traditional methods indicate that the features (baseline, pen pressure, word spacing, line spacing, and T-features) are not effective. A more interesting study on personality classification based on the Five Factor Model or prediction has been conducted for social behavior [13], financial behaviour [14], and user interface design [15].

Literature on personality classification using handwriting analysis shows a concentration on the old personality model. A recent review of automated handwriting analysis conducted by [16] and have mentioned the Five Factor Model, Myers-Briggs [17], Minnesota multiphasic personality inventory [18], and Enneagram [19]. Surprisingly, we have not found any literature that uses the HEXACO personality model. Some works have HEXACO for personality prediction using Random Forests and Particle Swarm Optimization methods [20]. However, their study is specifically designed for social media comments.

Karpova et al. have trained CNN to predict honesty from audio and video. They also built classifiers based on combined features extracted from video, audio, PPG, eye trackers with balanced subjects using the HEXACO-PI-R questionnaire for honesty and the Dark Triad for Machiavellianism, while setting them to a state of innocence or guilt. However, the mean accuracy obtained from the prediction is 0.596, with an f1-score obtained of 0.638 [26].

Peltzer et al. found that the HEXACO model has 31.97% more variation in workplace deviance (counterproductive work behavior that violates organizational norms) than the Big

 10.12928/ijio.v3i2.6242

Five model of 19.05%, so the HEXACO model seems a viable alternative to predict and explain workplace deviance rates [27].

Taghvaei et al. have conducted an experiment using a hybrid framework to predict the personality of social network users based on the Big Five model with the efficiency of fuzzy neural networks and deep neural networks from the perspective of different features and decisions fusion methods. The results obtained increased with an accuracy of up to 83.2%. However, the data used is a personality dataset sourced from social media [28]. Research Anglim et al. on the correlation of Schwartz's fundamental values with the broad and narrow traits of the HEXACO personality model using a sample of 1,244 adults. The developed regression model predicted each of the ten actual personality values reveals mean-adjusted multiple correlations of 0.39 for the HEXACO factor without honesty-humility. 0.45 for all HEXACO factors and 0.53 for HEXACO aspects. Substantial multiple-level correlation (>0.60) for power, universalism, and cooperation. However, Care needs to be taken in generalizing results back to the Big 5 framework. Likewise, the measure of personal values focuses on ten abstract matters identified as fundamental and vital across cultures [29].

Vries et al. combine a framework with insights from evolutionary, situational, and personality perspectives. The study reviews four personality models: (1) Common Personality Factors, (2) the Big Two, (3) the Big Five, and (4) the six-dimensional HEXACO model. they also use situational affordability and trait activation perspectives to offer an integrative model of HEXACO domain-specific situational affordability. The results suggest that the Situational, Trait, and Outcome Activation (STOA) mechanism can help explain the maintenance of individual differences in the six personality dimensions. However, because HEXACO emotionality is associated with high Big Five agreeableness but low emotional stability, it is unlikely to be related to intimate relationship satisfaction [30].

In this study, we aim to improve the effectiveness of a Convolutional Neural Network i.e. AlexNet model that correspond between handwriting images with HEXACO personality. To improve the effectiveness of the CNN, we utilize Particle Swarm Optimization method. From the literature described above, we may conclude that there are lack of studies that optimize Convolutional Neural Network using metaheuristics such as Particle Swarm Optimization in classifying HEXACO personality mode using handwriting images.

We choose the HEXACO model over Big Five model or Myers-Briggs model because the HEXACO model add rarely discussed personality which is the honesty-humility personality trait in addition to standard Big Five. As personality characterization is important for daily human communication, knowing this trait is extremely important to determine the proper acts and how to handle people with a tendency on manipulating others for personal gain and breaking rules. For organizations, this will help in assigning people to correct positions, tasks, and jobs for more efficient career development [17].

Classifying six-dimensional traits simultaneously and automatically from handwriting pose significant challenges. Previous work on personality classification is converged towards older psychological model such as the Five Factor Model while studies that employ the HEXACO model is limited to social media comments and not handwriting texts. Therefore, classifying the HEXACO personality model based on handwriting and machine learning remains unaddressed. The contribution of this work is an efficient, cost-effective and convolutional neural network called GraphoNet. Moreover, we utilize particle swarm optimization to find optimum parameters of GraphoNet. The proposed model is evaluated using the Indonesian handwriting dataset and compared to benchmarked AlexNet model [21]. The reported results will provide a baseline for future research work on predicting HEXACO personality.

METHOD

Our research proposes a convolutional neural network model called GraphoNet that is optimized by particle swarm optimization for predicting the type of human personality using

HEXACO based on handwriting images. Firstly, we collect our dataset of Indonesian language handwriting to support this study due to the lack of a public dataset that relates handwriting images with HEXACO. Detail of the dataset is given in the result Section.

The dataset is augmented using geometrical transformation of rotation and translation. The augmented is used to avoid overfitting during the training phase. Before training the network, we resize the images to shorten the computational time during training and divide all collected data into data training and data testing. The data for data training is used to train the network while testing data is used for evaluating the GraphoNet performances.

The training parameter includes initial learning rate, learn drop factor, regularization, validation frequency, and computational environment. However, in this study, we limit experimentation of parameter optimization into three parameters i.e. epoch, minibatch, and dropout rate. The detail of GraphNet architecture and HEXACO is given in the next subsection.

1. Proposed Convolutional Neural Network Architecture (GraphoNet)

We use Convolutional Neural Network as the classification method because it can learn features automatically at different resolutions throughout convolutional blocks. We called the proposed CNN as GraphoNet. It consists of 17 layers as follows:

- Image InputLayer ([32 32 3])
- convolution2dLayer(3,16,'Padding',1)
- convolution2dLayer(3,16,'Padding',1)
- batchNormalizationLayer
- reluLayer
- maxPooling2dLayer(2,'Stride',2)
- convolution2dLayer(3,32,'Padding',1)
- batchNormalizationLayer
- reluLayer
- maxPooling2dLayer(2,'Stride',2)
- convolution2dLayer(3,64,'Padding',1)
- batchNormalizationLayer
- reluLayer
- dropoutLayer(drop);
- fullyConnectedLayer(36)
- softmaxLayer
- classificationLayer

The process of AlexNet in Convolutional Neural Network begins with the input of an image with the standard image resolution size of 227 x 227 x 3. However, we vary the resolution down to 32 x 32 x 3 for training efficiency and to see if the network can process features at a lower resolution scale. Subsequently, there are 3 blocks of convolutional layers.

In the first block, the signal input (the image) is transferred to the first 2-D convolutional layer with 16 filters of size 3 x 3, and padding of size 1 along all edges of the layer input. We double the number of this layer as it can improve the validation accuracy [22]. The features are learned and extracted automatically within these layers. After that, the output of these layers is transferred to the first batch normalization layer to reduce the sensitivity of the network initialization. After normalization, the signal goes through ReLU and pooling layers. The ReLU layer determines whether the signal should continue or not by performing a thresholding operation where any values less than zero are set to zero while the pooling layer reduces the image size by using the downsampling operator. The second block has similar elements only that there is only 1 2-D convolutional layer. Another set of features is learned and extracted automatically at lower image resolution. The third block is similar to the second block minus the pooling layer and a similar process with the previous blocks is repeated.

10.12928/ijio.v3i2.6242

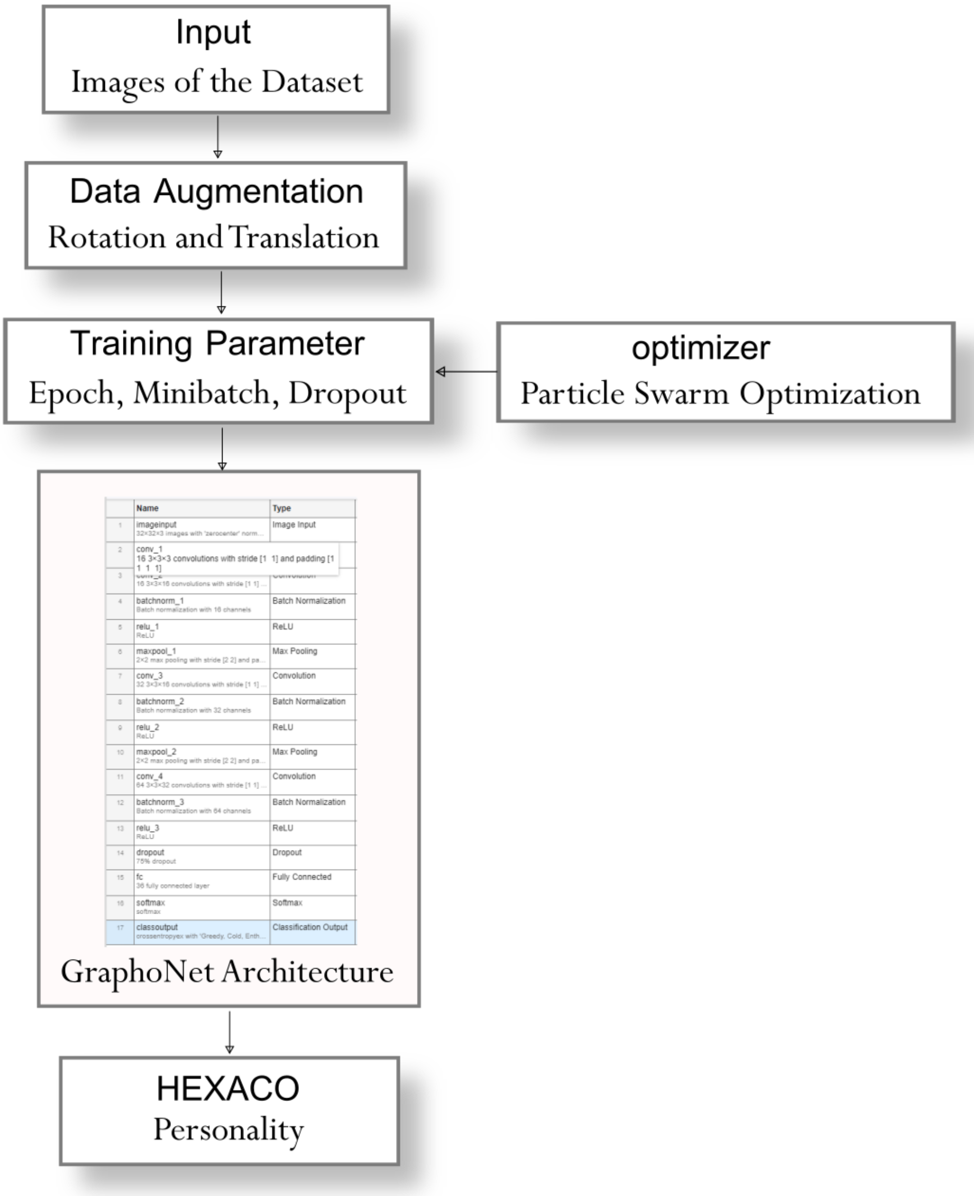

Figure 1. GraphoNet pipeline on predicting personality using HEXACO model

After some series of convolutional, normalization, activation and pooling processes, the signal is transferred to a dropout layer that sets input elements to zero with a given probability value (by default 50%). The output then goes to a fully connected layer with a density of 36 neurons associated with the total number of HEXACO personalities. The HEXACO personality is explained in the HEXACO Model subsection.

Then the signal moves to the softmax probability distribution function that normalizes the value of the signal. The final layer determines the personality output by computing the cross-entropy loss and weighted the result with mutually 36 exclusive classes.

2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a method that is inspired by the concept of and theory that birds or insects in a swarm, where they move around creating formations for purposes [23]. The swarm has collective intelligence for finding food, mate, and avoiding predators. We can model each particle to have a position that can be denoted as $x_i = (x_{i1}, x_{i2}, ..., x_{iD})$. While moving, each particle moves towards the optimal position guided by the position of the best particle and their own experience. Within the PSO model, each particle has three elements, momentum, cognitive and social components. As the momentum is based on the previous velocity which is represented as $v_i = (v_{i1}, v_{i2}, ..., v_{iD})$, the cognitive component is based on the heuristic that is represented by the position of the best member $p_i = (p_{i1}, p_{i2}, ..., p_{iD})$. The final component (social component) is based on the population swarm experience. Its value is the considered as best position of best member which is represented as $pbest$.

Then, the next particle's position is heuristically updated based on the rules of successive motion as given in (1).

$$x_{i+1} = x_i + v_{i+1} \quad (1)$$

Velocity v_{i+1} is a combination of three variables within the parameter of particle movement. Those variables are momentum, cognitive and social components as shown in (2).

$$v_{i+1} = 0.5 \cdot v_i + a_1 \cdot rand_1() \cdot (p_i - x_i) + a_2 \cdot rand_2() \cdot (p_{best} - x_i) \quad (2)$$

Variables a_1 and a_2 are the learning rates of both cognitive and social acceleration. The variables $rand_1$, $rand_2$ are random numbers with the range between 0 and 1 with a uniform distribution. The velocity variable v_i can also be limited to a limit between $[v_{max}, v_{max}]$. The pseudocode is given as follows:

```
Initialize the population
Do
    For each particle i = 1 to the N_th member
        if f(x_i) > f(p_i) then p_i = x_i
    if f(p_i) > f(p_best) then p_best = p_i
    For d = 1 to the D-dimension
        v_id = v_id + a_1·rand()·(p_id - x_id) + a_2·rand()·(p_best - x_id)
        v_i = maks (v_min, min (v_max, v_id))
        x_id = x_id + v_id
    next d
    next i
Until the termination criteria are met
```

The purpose of PSO is to optimize the CNN's parameters to achieve better classification accuracy [20]. We use PSO to optimize epoch, minibatch, and dropout during the training phase of GraphoNet. We based our experimentation on the previous work of [22]. Thus, the maximum iteration is set to 10, population 5, the maximum velocity is 5 and the minimum is -5.

3. HEXACO Model

HEXACO personality inventory is developed by Ashton and Lee [24] to assess personality dimensions that can be grouped into six basic dimensional traits. The detail description of these traits can be seen in [25]. We use 102 labels for personality classifications from handwriting images in this study. The labelling is directly performed by a trained and certified psychologist, which put each image taken as a dataset into the proper and correct label for classification [20]. Each dimension of HEXACO represents personality and character states identified in humans [25]. Every word within the "HEXACO" itself decribes the trait of human personality. "H" stands for honest and humidity, which refers to people who tend to avoid manipulating other

10.12928/ijio.v3i2.6242

individuals for personal gains and ego. “E” stands for emotionality, which means sensitivity towards stress, fear, and emotional support necessities. “X stands for extraversion, which refers to confidence and enjoyment in interpersonally and intrapersonally. “A” stands for agreeableness, which refers to tolerance tendency of individual towards specific occasions or people. “C” stands for Conscientiousness, which refers to consistency, management, and determination in achieving goals. Lastly, “O” stands for Openness to Experience, which refers to the will of absorbing and accepting changes and knowledge around environments where individuals are located [25].

4. Performance Evaluation

To evaluate the performance of the GraphoNet models, the accuracy metric which is derived directly from the confusion matrix is used for performance evaluation as given in Table I.

Table 1. The confusion matrix of 36 personalities from the HEXACO model

Personality Type	Prediction		
	Type 1	**Type 2**	**Type 36**
Type 1	x_{1-1}	x_{1-2}	x_{1-3}
Type 2	x_{2-1}	x_{2-2}	x_{2-3}
…			
Type 36	x_{36-1}	x_{36-2}	x_{36-3}

The accuracy value is obtained by comparing the number of correct prediction outputs against the three types. The total of true positive can be calculated using (1).

$$TTP_{all} = \sum_{j=1}^{36} x_{jj} \tag{3}$$

The variable x_{11} is the total true of Type 1, x_{22} is the total true of Type 2, and x_{33} is the total true of Type 3. The overall accuracy A can be calculated using (2).

$$A = \frac{TTP_{all}}{All} \tag{4}$$

Besides accuracy, we utilize computational time (CPU time) to measure the length of the training process. The experiments of this study were carried out using Intel (R) Core (TM) i9-6700HQ CPU @ 2.60GHz, 16GB RAM, 1TB HDD, and Nvidia GeForce GTX 950 GPU. As for software, we use Matlab 2022a working on Windows 10 Pro operating system. The reason for those specification selection is that due to its capability of training images faster with multiple GPU training.

RESULTS AND DISCUSSION

The dataset is collected or taken in random sampling out of populations from college students and office workers in the area of Pontianak City and Kubu Raya Regency in West Kalimantan Province. The places where dataset is collected from are STIEI Pontianak, STBA Pontianak, Tanjungpura University, and Sekolah Swasta Bina Bhakti Kubu Raya. We involved 323 individuals, out of which 162 were males and 161 females, with ages between 19 and 51 years old. All students and office workers are old enough to work, there are no underage individuals such as elementary, middle, or high school students. The data collected from the 323 images are in the form of handwriting taken from paper and scanned into images. However, there is 17 redundancy from the collected dataset which reduce the images to 293. These images were analyzed by graphologists to assess their traits based on six personality dimensions. The data are divided into training and testing sets with a ratio of 90% for training and 10% for testing.

The first experimentation was conducted on epoch parameters, image input size, minibatch, dropout, learning rate and CPU speed as shown in Table 2. We performed increments on epochs 5, 10, 25, 50, and 100 at image input size of 32 x 32 x 3, minibatch 31, learning 0.01, and no dropout layer. The CPU was set to normal speed and high speed. In general, the higher the epoch value, the more accuracy was obtained. The best result was achieved by GraphoNet at epoch 100 (GraphoNet100) with an accuracy of 65.62%. However, the CPU time was 6.5 times compared to epoch 50 (4.55 hours). Interestingly, our proposed network was able to beat standard CNN AlexNet (accuracy was only 25%). The implementation of AlexNet was left using default values given by the Matlab Deep Learning Toolbox (image input size 227 x 227 x 3, minibatch 10, dropout rate 50%, learning rate 0.0001. We have used parallel CPU and high-speed CPU mode for AlexNet but the training time is only faster at 420 seconds (4.44 hours). This is not surprising as the AlexNet was trained using images with 7 times larger resolution than the GraphoNet.

Table 2. Manual search experimentation of graphonet

CNN Model	Epoch	Input Size	Minibatch	Dropout (%)	Learning Rate	CPU	Accuracy (%)	CPU Time (seconds)
GraphoNet5	5	227 x 227 x 3	31	-	0.01	single (high-speed)		
GraphoNet5	5	32 x 32 x 3	31	-	0.01	single (high-speed)	9.38	280
GraphoNet10	10	32 x 32 x 3	31	-	0.01	Single (high-speed)	31.25	516
GraphoNet25	25	32 x 32 x 3	31	-	0.01	single (high-speed)	46.88	1356
GraphoNet50	50	32 x 32 x 3	31	-	0.01	single (normal)	62.50	2535
GraphoNet100	100	32 x 32 x 3	31	-	0.01	single (normal)	65.62	16406
AlexNet [21]	6	227 x 227 x 3	10	50	0.0001	single (high-speed)	25.00	382
AlexNet [21]	100	227 x 227 x 3	10	50	0.0001	parallel (high-speed)	21.88	15986

In the second experiment, we use Particle Swarm Optimization for optimizing the main GraphoNet parameters (epoch, minibatch, and dropout rate. Based on the previous study [22], the boundaries of the epoch were set between 0 and 50 while the minibatch was set between 10 and 40 and the dropout rate was set between 0 and 99%. Table 3 shows that the best epoch value was obtained at 25 while the best minibatch and dropout values were obtained at 30 and 52% respectively. However, we found that optimizing GraphoNet with PSO only reach 62.5% accuracy which was 3.12% lower than GraphoNet100. This lack of performance is suspected to lower the threshold of the epoch that was set to 50. Therefore, we use these best parameter values for training GraphoNet at 100 epochs.

Table 3. Experimentation of graphonet optimization using particle swarm optimization

CNN Model	epoch	input size	minibatch	Dropout (%)	learning rate	CPU	Accuracy (%)	CPU time (seconds)
GraphoNet + PSO	25	32 x 32 x 3	30 [a]	52 [a]	0.01	parallel (high-speed)	62.50	66325
PSO-optimized AlexNet [21]	100	227 x 227 x 3	30 [a]	52 [a]	0.01	parallel (high-speed)	6.25	6614
PSO-optimized GraphoNet	100	32 x 32 x 3	30 [a]	52 [a]	0.01	single (high-speed)	71.88	4857

10.12928/ijio.v3i2.6242

Interestingly, GraphoNet was able to reach 71.88% accuracy with only 4857 seconds of training time. Figure 2 shows the training progress of GraphoNet Optimized using Particle Swarm Optimization. Besides a decent accuracy for classifying 36 possible HEXACO models, the network has been able to improve the training by 3.38 times faster in comparison with GraphoNet100. This result was also achieved using only a single CPU. When we used the optimized parameters for AlexNet, the results were worse than the default values given by the Matlab toolbox. This is not surprising as the PSO was optimized for GraphoNet and not for the standard AlexNet.

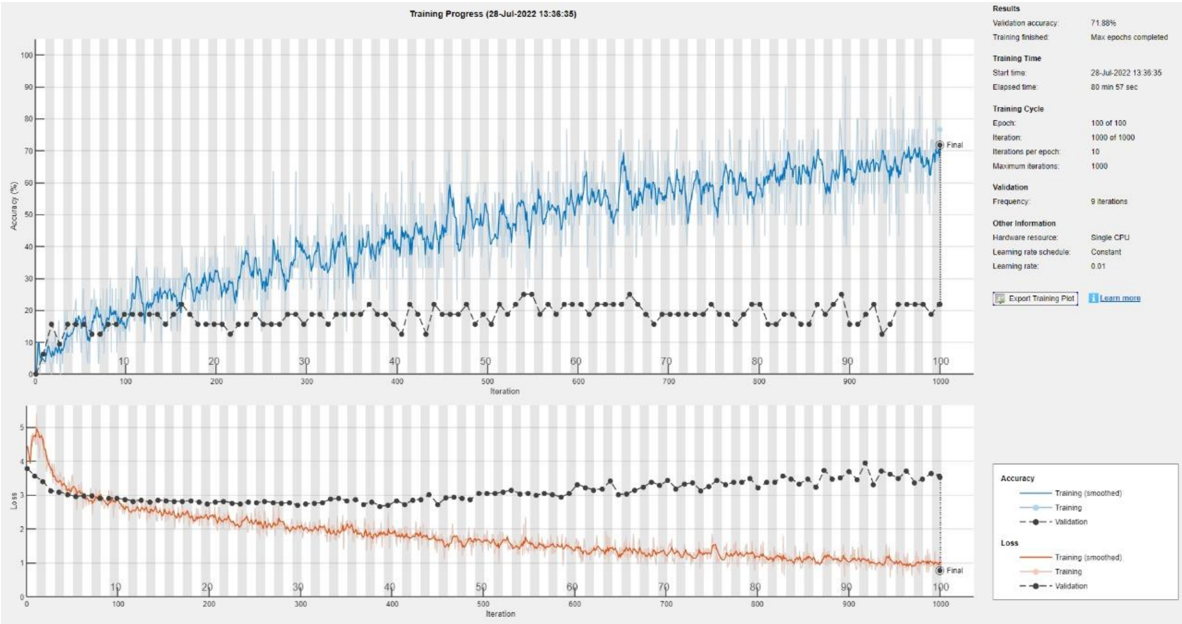

Figure 2. The training of graphonet optimized using particle swarm optimization

CONCLUSION

The result and discussion above shows that the result of implementing Particle Swarm Optimization on GraphoNet was successfully able to improve accuracy to 71.88% compared to AlexNet with only 25% accuracy. This performance is significantly due to the ability of PSO to optimize dropout rate values. Thus, the proposed method is promising for classifying six personality traits or HEXACO model simultaneously through handwriting images. There is some to improve in this study. Future research needs a larger dataset as HEXACO learning spaces can reach more than 36 types of personalities because each character can be divided into several values. This study is limited to solely optimising epoch, minibatch, and dropout rate. However, other parameters such as learning rate, size of the image input, and data augmentation can be optimized to improve the convolutional neural network performances.

ACKNOWLEDGMENT

We would like to show our gratitude to Esa Unggul University for allowing us to conduct and write a study or research on this topic.

REFERENCES

[1] F. Rizvi and M. S. H. Khiyal, “Personality prediction through offline handwriting analysis,”

J. Multidiscip. Eng. Sci. Stud., vol. 3, no. 1, pp. 1282–1288, 2017.
[2] K. Chaudhari and A. Thakkar, "Survey on handwriting-based personality trait identification," *Expert Syst. Appl.*, vol. 124, pp. 282–308, 2019.
[3] N. Punetha, A. K. Pal, and V. Sharma, "Behavior Prediction of Human by Signature and Handwriting Analysis Using Matlab," 2020.
[4] M. Gavrilescu and N. Vizireanu, "Predicting the Big Five personality traits from handwriting," *EURASIP J. Image Video Process.*, vol. 2018, no. 1, pp. 1–17, 2018.
[5] A. R. Pathak, A. Raut, S. Pawar, M. Nangare, H. S. Abbott, and P. Chandak, "Personality analysis through handwriting recognition," *J. Discret. Math. Sci. Cryptogr.*, vol. 23, no. 1, pp. 19–33, 2020.
[6] A. U. Rahman, "Towards Development of Computational Methods for Handwriting Analysis with Focus on Writer Identification, Personality Prediction, and Emotion Detection," Ghulam Ishaq Khan Institute of Engineering Sciences and Technology, 2022.
[7] M. S. Anari, K. Rezaee, and A. Ahmadi, "TraitLWNet: a novel predictor of personality trait by analyzing Persian handwriting based on lightweight deep convolutional neural network," *Multimed. Tools Appl.*, vol. 81, no. 8, pp. 10673–10693, 2022.
[8] J. E. Valdez-Rodr\'\iguez, H. Calvo, and E. M. Felipe-Riveron, "Handwritten Texts for personality identification using convolutional neural networks," in *International Conference on Pattern Recognition*, 2018, pp. 140–145.
[9] S. H. Fatimah, E. C. Djamal, R. Ilyas, and F. Renaldi, "Personality features identification from handwriting using convolutional neural networks," in *2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, 2019, pp. 119–124.
[10] N. Lemos, K. Shah, R. Rade, and D. Shah, "Personality prediction based on handwriting using machine learning," in *2018 International Conference on Computational Techniques, Electronics and Mechanical Systems (CTEMS)*, 2018, pp. 110–113.
[11] A. Chitlangia and G. Malathi, "Handwriting analysis based on histogram of oriented gradient for predicting personality traits using SVM," *Procedia Comput. Sci.*, vol. 165, pp. 384–390, 2019.
[12] A. A. Elngar, N. Jain, D. Sharma, H. Negi, A. Trehan, and A. Srivastava, "A deep learning based analysis of the big five personality traits from handwriting samples using image processing," *J. Inf. Technol. Manag.*, vol. 12, no. Special Issue: Deep Learning for Visual Information Analytics and Management., pp. 3–35, 2020.
[13] S. Ghosh, P. Shivakumara, P. Roy, U. Pal, and T. Lu, "Graphology based handwritten character analysis for human behaviour identification," *CAAI Trans. Intell. Technol.*, vol. 5, no. 1, pp. 55–65, 2020.
[14] S. Thomas, M. Goel, and D. Agrawal, "A framework for analyzing financial behavior using machine learning classification of personality through handwriting analysis," *J. Behav. Exp. Financ.*, vol. 26, p. 100315, 2020.
[15] W. Ilmini and T. G. I. Fernando, "Computational personality traits assessment: A review," in *2017 IEEE International Conference on Industrial and Information Systems (ICIIS)*, 2017, pp. 1–6.
[16] R. K. Samsuryadi and F. S. Mohamad, "Automated handwriting analysis based on pattern recognition: A survey," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 1, pp. 196–206, 2021.
[17] M. Gavrilescu, "Study on determining the Myers-Briggs personality type based on individual's handwriting," in *2015 E-Health and Bioengineering Conference (EHB)*, 2015, pp. 1–6.
[18] B. Fallah and H. Khotanlou, "Identify human personality parameters based on handwriting using neural network," in *2016 Artificial Intelligence and Robotics (IRANOPEN)*, 2016, pp. 120–126.
[19] D. Pratiwi, G. B. Santoso, and F. H. Saputri, "Personality type assessment system by using enneagram-graphology techniques on digital handwriting," *Int. J. Comput. Appl.*,

 10.12928/ijio.v3i2.6242

vol. 147, no. 11, 2016.

[20] I. Ramadhan, H. Akbar, G. Firmansyah, and A. Mulyo, “Predictions of Six Personality Characters (HEXACO) from Social Media using Random Forest Classifier and Particle Swarm Optimization,” 2021.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” *Adv. Neural Inf. Process. Syst.*, vol. 25, pp. 1097–1105, 2012.

[22] H. Akbar, N. Anwar, S. Rohajawati, A. Yulfitri, and H. S. Kaurani, “Optimizing AlexNet using Swarm Intelligence for Cervical Cancer Classification,” in *2021 International Symposium on Electronics and Smart Devices (ISESD)*, 2021, pp. 1–6.

[23] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proceedings of ICNN’95-international conference on neural networks*, 1995, vol. 4, pp. 1942–1948.

[24] M. C. Ashton and K. Lee, “The HEXACO--60: A short measure of the major dimensions of personality,” *J. Pers. Assess.*, vol. 91, no. 4, pp. 340–345, 2009.

[25] K. Lee and M. C. Ashton, “The Hexaco Personality Inventory - Revised, A Measure Of The Six Major Dimensions Of Personality,” 2009. Available : https://hexaco.org/scaledescriptions

[26] Karpova, V., Popenova, P., Glebko, N., Lyashenko, V., & Perepelkina, O. (2020). “Was It You Who Stole 500 Rubles?” - The Multimodal Deception Detection. Companion Publication of the 2020 International Conference on Multimodal Interaction, 112–119. Available : https://doi.org/10.1145/3395035.3425638

[27] Pletzer, J. L., Bentvelzen, M., Oostrom, J. K., & de Vries, R. E. (2019). A meta-analysis of the relations between personality and workplace deviance: Big Five versus HEXACO. *Journal of Vocational Behavior*, *112*(February), 369–383. Available : https://doi.org/10.1016/j.jvb.2019.04.004

[28] Taghvaei, N., Masoumi, B., & Keyvanpour, M. R. (2021). A Hybrid Framework for Personality Prediction based on Fuzzy Neural Networks and Deep Neural Networks. *Technology Journal of Artificial Intelligence and Data Mining*, *9*(3), 283–294. Available : https://doi.org/10.22044/jadm.2021.10583.2197

[29] Anglim, J., Knowles, E. R. V., Dunlop, P. D., & Marty, A. (2017). HEXACO personality and Schwartz’s personal values: A facet-level analysis. *Journal of Research in Personality*, *68*, 23–31. Available : https://doi.org/10.1016/j.jrp.2017.04.002

[30] de Vries, R. E., Tybur, J. M., Pollet, T. V., & van Vugt, M. (2016). Evolution, situational affordances, and the HEXACO model of personality. *Evolution and Human Behavior*, *37*(5), 407–421. Available : https://doi.org/10.1016/j.evolhumbehav.2016.04.001