Handwriting Analysis for Personality Trait Features Identification using CNN

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2022 International Conference on Data Science and Its Applications (ICoDSA) | 978-1-6654-8665-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICoDSA55874.2022.9862910

***Abstract*—Handwriting analysis is an approach to get information through the handwriting. It extremely useful information, for instance in personality traits identification. The information came from the feature extracted from the handwriting. This feature can be size, slantness, pressure, and so forth. In this research, handwriting analysis is through the AND dataset that provide handwriting dataset along with feature label while most public dataset has nothing with it. By using the Coonvolutional Neural Networks (CNN) potentiality in capturing and recognizing global features, there are 15 models had built in this research in accordance with each feature and divided into three group by its number of types. After built a simple CNN architecture by only conduct two convolution layer, overall result show fair enough performance where the highest rate of accuracy is 80.88%. Furthermore, there are three best features had recognized, which is "entry stroke 'A'", "size", and "slantness", where the last two is naturally global features. However, the fact that handwriting image data cannot be oversampled which can lead to the bias result, than the imbalance data becomes a problem in this research that reduced the model performance.**

Keywords*—*handwriting analysis, cnn, personality traits.

I. Introduction

Handwriting analysis is a study to identify some features in handwritten and use it as an information to various application, for instance in writer identification, gender classification, personality traits identification, and so on. This information typically generated by graphologist and depend on graphologist skill to accomplish this task. To get standard information from handwritten, a computer can be used to do this task, for instance in computer vision field. This analysis can be done by capture handwritten as an image and analyze it by using some related method. For personality traits classification, the information from some feature can be used such as baseline, slant, word and character attribute so on as a local feature shown in Table I. On others side, some feature can appear in global.

To identify personality traits, a standard scale can be conducted. The scale is grouped some feature into some personality traits. Difference scale used difference feature in their scale, and this be the way to select some feature. There is common scale can be used in identify personality traits, they are Minnesota Multiphasic Personality Inventory (MMPI), Myer-Briggs Type Indicator (MBTI), Enneagram, Five Factor Model (FFM) also called Big Five Model and so forth. But the FFM consider to be a stable method to classify personality traits in computer manner.

There are two approaches to identify personality trait along with its feature as handwriting analysis task, they are machine learning (conventional) approach and deep learning approach. In [3, 7, 21-23] they use support vector machine (SVM) with accuracy above 80%. [2, 3] use neural network with promising performance which is around 80% and k-NN as well [3]. In deep learning, it is commonly use Convolutional Neural Network (CNN) as its method. It has a promising result [11, 24, 25]. In [24] it uses baseline, spacing, and slant feature. while [11, 25] use baseline, slant, pressure, size, margin, and zone.

CNN is a method in deep learning that work similarly with Neural Networks (NN). This has an architecture as NN has and use feedforward method to get the output and updated all the weight and bias by using backpropagation. The difference come from the convolution process as it came out in its name. this process made the method find or extract the feature by itself. The feature extracted as a global feature by using several filters and connected at every layer become a high-level feature. That is why this method become so powerful nowadays. But the problem come to this method is the deeper it learns than the more it takes a cost in computation. Although there are some devices can manage this by using such latest technology, say high performance GPU, but we can merely depend on it.

TABLE I. List of Handwriting Features

No.	Handwriting Features
1	Baseline [1-9]
2	Size [7, 8, 10-13]
3	Pressure [3, 6, 7, 12, 14, 15]
4	Connecting Strokes [2, 3, 14]
5	Slant [1-3, 8, 10, 12-16]
6	Letter Spacing [7, 11]
7	Word Spacing [7, 11]

8	Line Spacing [7, 11]
9	Letter 'i' [10, 17, 18]
10	Margin [1, 9, 11, 19, 20]
11	Letter 't' [1, 2, 3, 14, 16, 17]
12	Letter 'f' [2, 3, 14]
13	Speed [7, 17]

There are two kinds of datasets in handwriting analysis which is the private and the public dataset. There is no specific public dataset which can be used directly to identify personality traits. Many researchers use a graphologist, psychologist, and scale to label the data in accordance with personality traits identification requirement, commonly it is labeled with writer or text itself. However, [26] set a dataset along with the label as the handwriting features. It has 15 group of features. It is labeled into two, three and four type of features and it suitable for personality traits identification. Though this more suitable, it only using one word as the name of dataset came from, that is AND word. But this gives an opportunity to utilize a global feature extractor to recognize or identify these features. And it is interesting using this dataset as commonly global feature use baseline, spacing, pen pressure, zone, slant and etc., that is naturally a global feature. Meanwhile, in this dataset they are a stroke features for instance that not naturally as a global feature.

Afterward, in this research use AND dataset to identify handwriting features. This research tries to set a simple CNN architecture and make it general by using the same architecture or model in each feature, which is 15 model. A simple architecture means not set a deep CNN it only contains two convolution layers as the input data not a large-scale image. This approach is conducted in order to get an ease use of CNN and also still has use the benefit of CNN that is well method in identify image by using global feature. For detail in this work, it will explain in the next following chapter.

II. Convolutional Neural Networks (CNN)

Similar with Neural Networks (NN), Convolutional Neural Networks (CNN) do the same proses as it generally, except how CNN figure out the feature by itself. The CNN utilize convolution to extract feature from the input data, that the convolution name came out. As the NN has a layer in its architecture, there are three kind of layer CNN has, they are convolution, pooling and fully connected layer. The following paragraph described these layers [11, 24, 25].

A. Convolution Layer

Given two functions f and g, then the convolution of the two at certain point x_t is an integral product of the two where one of them is flipped and shifted. For instance, set g is an even function and shifted in $[x_0, x_1]$, the convolution $(f * g)(x)$ is denoted by equation (1) where the convolution is area under the product of f and g in $[x_0, x_1]$. Noted, that $g(x) = g(-x)$ as it an even function. In the signal processing field, the convolution is also called a superimposition proses of two signals (say f and g, where g called kernel function). Furthermore, in 2D the equation (1) become (2) where f called an image and g is a filter.

As an image come in discrete form (sampled from analog image: *acquisition process*) this proses expressed in equation (3). In addition, for a color image (RGB), the convolution is sum of convolution result from each channel and called a feature map in CNN.

$$(f * g)(x_t) = \int_{x_0}^{x_1} f(x) g(x_t - x)\, dx \quad (1)$$

$$(f * g)(x_t, y_t) = \int_{y_0}^{y_1} \int_{x_0}^{x_1} f(x, y) g(x_t - x, y_t - y)\, dx\, dy \quad (2)$$

$$(f * g)(x_t, y_t) = \sum_{y_t=y_0}^{y_1} \sum_{x_t=x_0}^{x_1} f(x, y) g(x_t - x, y_t - y) \quad (3)$$

B. Pooling Layer

By using this layer, the input feature map is reduced into smaller feature map. There are several methods to do this task, for instance max pooling, average pooling, global max pooling and global average pooling. It works similar with convolution except it only set new value or sub sampling by using max value. For average pooling, it works with average value. However, global max and average pooling reduce input feature map into single value (whether it max or average value). There is no filter size for them, it covers all value from input feature map.

C. Fully Connected Layer

This layer is a Neural Networks (NN) layer. The input of this layer is a vector in $\boldsymbol{R}^n$ transformed from feature map (called flatten) while n as number of input node. The output of this layer is output of CNN. It can be one or more nodes on classification task it depends on binary or multiple classification.

D. Architecture

Naturally CNN work like an NN, it has an architecture, weight and bias for every connected layer. In convolution layer, the filters or kernels is same as a weight in NN. The result of convolution along with bias is transformed by activation function. This process continues until it reached the flatten layer and than it goes just as an NN. How CNN updated their weight is using the same method as NN did, that is backpropagation. It updated their weight using gradient to find a global minima of loss function, but nowadays it commonly used Adam optimizer method to do this task.

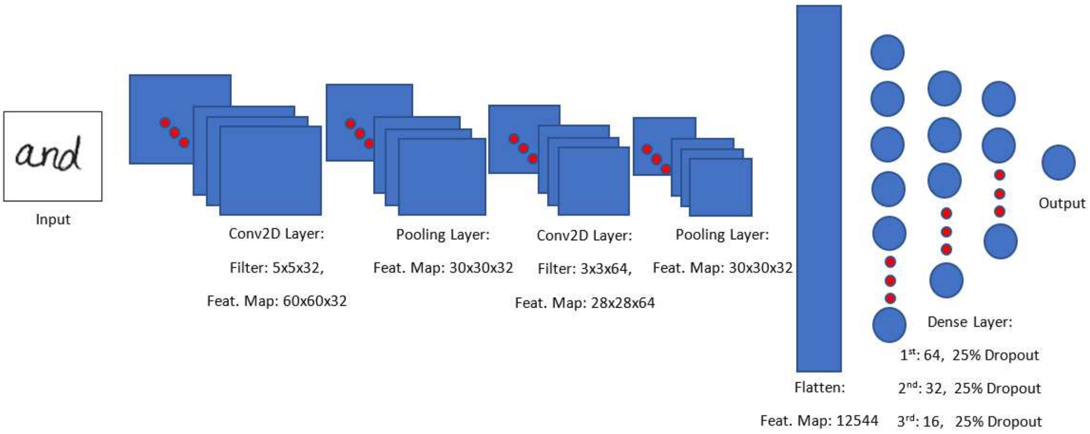


Fig. 1. CNN architecture.

III. Experiment and Result

A. And Dataset

In dataset used in this research is XAI-AND dataset or rather called And Dataset. It is a public dataset consist of 15.518 "AND" handwriting image cropped from CEDAR dataset. This dataset is written by 1567 writer and grouped in into 15 categories of handwriting feature. In each category is divided into two, three or four types. Most of this dataset consist of two type handwriting features for instance pen pressure with strong and medium type. The rest of two type handwriting features are tilt, entry stroke 'a', is lowercase, constancy, word formation of 'n', and is continuous. For the rest, there are 4 group for three type handwriting features and 3 for the four types. Three type handwriting features consist of size, dimension, letter spacing, and staff of 'd'. Four consist of slantness, staff of 'a', and exit stroke 'd'.

The sample of each feature from AND dataset shown by figure 2 arranged from top left to bottom right. Furthermore, by only use one word it can be interesting to recognize this type by using global feature extraction and it goes through this research.

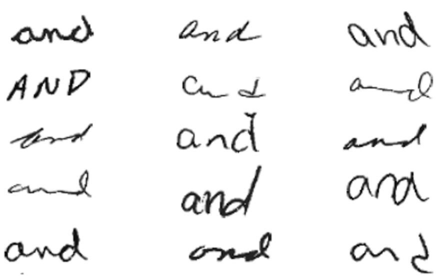


Fig. 2. AND dataset.

B. CNN Model

This research using simple CNN architecture (model), shown in figure 1 and use Google Collab notebook with standard specification form as a platform. Started from input image, 64×64 grayscale, first layer generates 32 filters with 5×5 size along with bias, then there are $(5 \times 5 + 1) \times 32$ trainable parameters set. This layer brought out 60×60 feature maps since convolution process has no padding included. After this, it is reduced into 30×30 by pooling layer using max pooling method. In second convolution layer, 64 filters are generated with 3×3 size along with bias and it set $(3 \times 3 \times 32 + 1) \times 6$ trainable parameters. Hereinafter, 28×28 feature maps are generated and reduced into 14×14 by pooling layer with same method. All feature maps set into feature vector set as $14 \times 14 \times 16$ features. This stage is called flatten layer as an input into dense layer. Afterwards, there are 12544×64 trainable parameters and drop 16 out of it as dropout layer set. It repeatedly into next two dense layer and there are 824,833 trainable parameter as shown by figure 3.

In last stage (output), it divided into three shapes, in particular one node for binary classification, three and four nodes for multilabel classification as the dataset label state it. There are 15 models were trained in accordance with the number of handwriting features where the "simple" term emerged by only two convolution layers that the model have on it. Set all initial weight (filters) and bias using Xavier initialization, where the bias set to zeros and weight generate by uniform distribution in $\left[-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}\right]$ with n as filter size ($n \times n$).

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 60, 60, 32)	832
max_pooling2d (MaxPooling2D)	(None, 30, 30, 32)	0
conv2d_1 (Conv2D)	(None, 28, 28, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 14, 14, 64)	0
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 64)	802880
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 16)	528
dropout_2 (Dropout)	(None, 16)	0
dense_3 (Dense)	(None, 1)	17

Total params: 824,833
Trainable params: 824,833
Non-trainable params: 0

Fig. 3. CNN trainable parameters.

Shown by Table II that there is no significance difference in each epoch (except five model: pen-pressure, is continuous, size, dimension, staff of 'D', slantness), this research use only 5 epochs on each model. In training process, all data are included in each epoch means there is no batch set. And the last, this model used Adam optimizer to update all the weight and bias in it.

C. Result

Trying to make model general, this research using 15 model with same architecture (except the output of course). In two types handwriting feature (model number 1, 2, …, 8), this model achieves better result in training shown by Table II in last epoch. It achieves almost above 70% accuracy, though the last two is not. It also follows by the three-type handwriting feature. However, in the four-type handwriting feature there is only one model that could follow the two before. Rate all this training perform show that this approach (in this research) achieves a fair result in training model that is 74.81%. The highest perform is on "is lower" handwriting feature, it gives 98.48% accuracy, and it is followed by "entry stroke A" handwriting feature at 97.69% Accuracy. The lower perform is shown by "exit stroke of 'D'" handwriting feature. It the only one model that has below fifty percent accuracy, which is 43.94% and also it never changes in any epoch. Came into the test phase, the model can be grouped into three groups and described as follows:

1. The two-type handwriting features model

    This model is the highest accuracy in rate, it is 80.88%, while the "is lower" and "entry stroke 'A'" gift high accuracy as the same their training perform, that is 99% and 97% shown by Table III. But the better one is the second with stable f1-score. As it has high accuracy in rate, but this group has fair f1-score, 59.06% since there is zero score at a couple of features. This zeros score come mostly in high ratio of imbalance data. For instance, in tilt handwriting feature it has 3354 normal data and 717 tilted data (handwriting).

TABLE II. TRAINING PERFORMANCE

No.	Model	Accuracy (%)					Difference in each epoch (Rate)
		Epoch-1	Epoch-2	Epoch-3	Epoch-4	Epoch-5	
1	Pen Pressure	77.36	85.70	86.01	85.66	87.00	2.585
2	Is lower	98.07	98.48	98.46	98.48	98.48	0.1125
3	Is continuous	76.60	85.12	87.96	89.09	89.90	3.325
4	Tilt	79.49	80.75	80.75	80.75	80.75	0.315
5	Entry Stroke 'A'	94.64	95.72	96.85	97.38	97.69	0.7625
6	Formation of 'N'	76.01	77.26	77.26	77.26	77.26	0.3125
7	Word Formation	54.06	56.36	56.36	56.60	56.76	0.675
8	Constancy	58.06	60.57	60.60	60.59	60.59	0.6375
9	Letter Space	50.58	51.48	51.93	52.55	54.36	0.945
10	Size	63.21	70.63	72.29	73.77	75.43	3.055
11	Dimension	73.03	77.85	80.46	81.20	83.12	2.5225
12	Staff of 'D'	66.54	80.83	84.14	85.91	87.20	5.165
13	Slantness	54.74	65.54	67.22	68.72	71.23	4.1225
14	Staff of 'A'	56.24	58.37	58.37	58.37	58.37	0.5325
15	Exit Stroke of 'D'	43.94	43.94	43.94	43.94	43.94	0
	Rate	68.17	72.57	73.51	74.02	74.81	1.67

TABLE III. TWO-TYPE HANDWRITING FEATURES TESTING PERFORMANCE

Feature	Type	Accuracy (%)	Precision (%)	Recall (%)	f1-score (%)	Data
Pen Pressure	Strong	87	84	83	83	1665
	Medium		88	89	89	2406
Is lower	No	99	0	0	0	60
	Yes		99	100	99	4011
Is continuous	No	89	91	73	81	1347
	Yes		88	96	92	2724
Tilt	Normal	82	82	100	90	3354
	Tilted		0	0	0	717
Entry Stroke 'A'	No Stroke	97	98	99	99	3809
	Down Stroke		83	72	77	262
Formation of 'N'	No Format	76	0	0	0	957
	Normal		76	100	87	3114
Word Formation	Not well formed	57	57	100	73	2331
	Well formed		0	0	0	1740
Constancy	Irregular	60	0	0	0	1638
	Regular		60	100	75	2433
Rate		80.88	56.63	63.25	59.06	

TABLE IV. THREE-TYPE HANDWRITING TESTING PERFORMANCE

Feature	Type	Accuracy (%)	Precision (%)	Recall (%)	f1-score (%)	Data
Letter Space	Less	58	60	24	34	904
	Medium		56	91	70	2137
	High		70	19	29	1030
Size	Small	76	78	60	68	957
	Medium		75	81	78	2138
	Large		76	81	78	976
Dimension	Low	69	84	51	64	1208
	Medium		69	75	72	2134
	High		56	80	66	729
Staff of 'D'	No Staff	86	68	25	36	405
	Retraced		82	95	88	2027
	Loopy		94	89	91	1639
Rate		72.25	72.33	64.25	64.5	

2. The three-type handwriting features model

With the rate accuracy is 72.25% and 64.5% score, it has a fair enough performs shown by Table VI. This group has a better f1-score from the rest. It shows this model is the stable one and it does not surprise that it has no zero f1-score in there. This comes a bit better overcome the imbalance data. In this group there are two features has higher accuracy, they are "staff of 'D' and 'size', but the better one is the second with more stable in f1-score.

3. The four-type handwriting features model

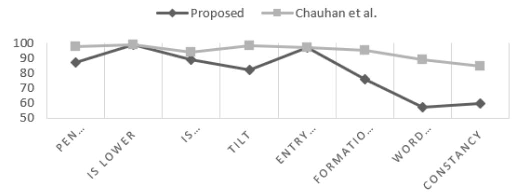
The lower one come from this group, it has 58.33% accuracy with the 31.58% f1-score shown by table V. Same as before it come up from the high ratio imbalance data, while the 'slantness' gift a better perform, 72% accuracy with a fair stable f1-score. All of the better perform in f1-score come out from the high group of data.

TABLE V. FOUR TYPE HANDWRITING TESTING PERFORMANCE

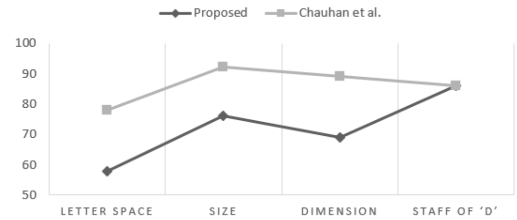
Feature	Jenis	Accuracy	Precision	Recall	f1-score	Data
Slantness	Normal	72	80	81	81	2114
	Slight Right		60	74	67	1195
	Very Right		63	51	56	451
	Left		81	27	40	311
Staff of 'A'	No staff	59	0	0	0	731
	Retraced		59	100	74	2386
	Loopy		0	0	0	266
	Tented		0	0	0	688
Exit Stroke of 'D'	No Stroke	44	0	0	0	969
	Downstroke		44	100	61	1799
	Curved up		0	0	0	524
	Straight across		0	0	0	779
Rate		58.33	32.25	36.08	31.58	

TABLE VI. COMPARISON RESULT

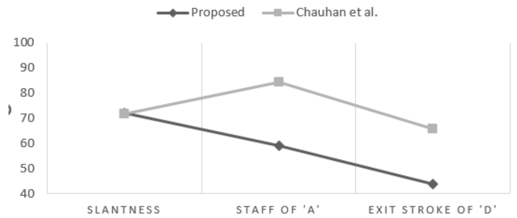
Type	Feature	Proposed (%)	Chauhan et al. (%)
Two-type Handwriting Features	Pen Pressure	87	98
	Is lower	**99**	**99**
	Is continuous	89	93.75
	Tilt	82	98.44
	Entry Stroke 'A'	**97**	**97**
	Formation of 'N'	76	95.31
	Word Formation	57	89.06
	Constancy	60	84.38
Rate		80.875	94.3675
Three-type Handwriting Features	Letter Space	58	78.13
	Size	76	92.19
	Dimension	69	89.06
	Staff of 'D'	**86**	**85.94**
Rate		72.25	86.33
Four-type Handwriting Features	**Slantness**	**72**	**71.88**
	Staff of 'A'	59	84.38
	Exit Stroke of 'D'	44	65.63
Rate		58.33	73.96



(a)



(b)



(c)

Fig. 4. Graphic Comparison Result

Comparing our research to [27] where the accuracy as the main metric (shown by Table VI), there are same several results particularly is lower, entry stroke 'A', staff of 'd' and slantness. Generaly, our research show the same highest accuracy in two-type and four-type handwriting features, except three-type handwriting feature where the highest accuracy is at size feature. The Graphic shown by figure 4 describe the same pattern that indicate the same problem. By this comparison it is possible to get a simple CNN where the dense layer can be modify with other method than typical neural networks.

IV. Conclusion

At the end this research has it final statement, that the CNN model used in this research is more suitable for two and three type handwriting features. The model performed 80.88% accuracy and 72.25% Accuracy for them. The lower one is on four-type handwriting features model, as it shown 58.33% accuracy.

Even if it has high accuracy rate, but it not the same with f1-score. Compare with the three-type handwriting features model, it more stable the three-type handwriting features model. It has 64.25% f1-score, better than the two-type handwriting features model. furthermore, the two-type handwriting features model has zero f1-score for a few features. It most came up from the imbalance data with high ratio.

There are three handwriting features consider to be the best recognized of each type handwriting group, they are "entry stroke 'A'" (two type), "size" (three type), and "slantness" (four type). It easy to understand that the last two it is naturally having a global feature. Set the same architecture with the simple one, it eases of use, but it only had a fair perform in order to recognize the handwriting feature. Moreover, it not suitable for four type handwriting feature and imbalance data.

For the last one, generating some geometry transformation to get balance data cannot be conducted due to real situation data required in handwriting analysis. Some pseudo data can give bias in type of feature, say slantness. Therefore, this issue, can be an open area to solve, because it is not easy to get balance data as a volunteer that we gather around may come not in the same group type of handwriting.

References

[1] P. Joshi, A. Agarwal, A. Dhavale, R. Suryavansi, and S. Kodolikar, "Handwriting Analysis for Detection of Personality Traits using Machine Learning Approach", Int. J. Comput. Appl., vol. 130, no. 15, pp. 40-45, 2015, doi: 10.5120/-ijca2015907189.

[2] M. Gavrilescu, "Study on determining the Myers-Briggs personality type based on individual's handwriting", in the 5th IEEE International Conference on E-Health and Bioengineering - EHB2015, doi: 10.1109/EHB.2015.7391603.

[3] M. Gavrilescu, "3-Layer architecture for determining the personality type from handwriting analysis by combining neural networks and Support Vector Machines", UPB Sci. Bull. Ser. C Electr. Eng. Comput. Sci., vol. 79, no. 4, pp. 135-152, 2017.

[4] S. Asra and S. D.C, "Personality Trait Identification Using Unconstrained Cursive and Mood Invariant Handwritten Text" Int. J. Educ. Manag. Eng., vol. 5, no. 5, pp. 20-31, 2015, doi: 10.5815/ijeme.2015.05.03.

[5] S. Nagar, S. Chakraborty, A. Sengupta, J. Maji, and R. Saha, "An efficient method for character analysis using space in handwriting image", in Proceedings - 2016 6th International Symposium on Embedded Computing and System Design, ISED 2016, pp. 210-216, 2016, doi: 10.1109/ISED.2016.-7977084.

[6] A. Bal and R. Saha, "An Improved Method for Handwritten Document Analysis using Segmentation, Baseline Recognition and Writing Pressure Detection", in Procedia Computer Science, vol. 93, pp. 403-415, 2016, doi: 10.1016/-j.procs.2016.07.227.

[7] A. M. Bobade and P. N. N. Khalsa, "Character Revealing Handwriting Analysis based on Segmentation method using Support Vector Machine", Int. J. Electron. Commun. Soft Comput. Sci. Eng., pp. 203-207, 2015, doi: 10.5120/1256-1758.

[8] D. Pratiwi, G. Budi, and F. Hana, "Personality Type Assessment System by using Enneagram-Graphology Techniques on Digital Handwriting", Int. J. Comput. Appl., vol. 147, no. 11, pp. 9-13, 2016, doi: 10.5120/ijca2016911181.

[9] S. Hashemi, B. Vaseghi, and F. Torgheh, "Graphology for Farsi Handwriting Using Image Processing Techniques", IOSR J. Electron. Commun. Eng. Ver. I, vol. 10, no. 3, pp. 2278-2834, 2015. doi: 10.9790/2834-10310107

[10] A. Sen and H. Shah, "Automated Handwriting Analysis System using Principles of Graphology and Image Processing", in ICIIECS, 2017, doi: 10.1109/ICIIECS.2017.8276061.

[11] D. Sony and R. Sawant, "Identifying Human Behavior Characteristics using Handwriting Analysis", Int. Res. J. Eng. Technol., vol. 06, no. 04, pp. 4436-4439, 2019, doi: 10.1109/ICIIC.2010.29.

[12] S. Mukherjee and I. De, "Feature extraction from handwritten documents for personality analysis," in 2016 International Conference on Computer, Electrical and Communication Engineering, ICCECE 2016, 2016, doi: 10.1109/ICCECE.2016.8009580.

[13] R. Kumar, K. K. Ravulakollu, and R. Bhat, "Fuzzy-Membership based writer identification from handwritten devnagari script", J. Inf. Process. Syst., vol. 13, no. 4, pp. 893-913, 2017, doi: 10.3745/JIPS.02.0018.

[14] M. Gavrilescu and N. Vizireanu, "Predicting the Big Five personality traits from handwriting", EURASIP J. Image Video Process., 2018, doi: 10.1186/s13640-018-0297-3.

[15] K. N. Lakshmi, A. Keerthana, and P. R. Lakshmi, "Handwriting Analysis Based Human Personality Prediction Using Sugeno Fuzzy Model," Int. J. Sci. Eng. Res., vol. 8, no. 5, pp. 105-110, 2017.

[16] P. Joshi, P. Ghaskadbi, and S. Tendulkar, "A Machine Learning Approach to Employability Evaluation Using Handwriting Analysis", in ICAICR, pp. 253-263, 2018, doi: 10.1007/978-981-13-3140-4_23.

[17] E. C. Djamal and Febriyanti, "Identification of speed and unique letter of handwriting using wavelet and neural networks", in International Conference on Electrical Engineering, Computer Science, and Informatics (EECSI), vol. 2, no. August 2015, pp. 74-78. doi: 10.11591/eecsi.v2.493

[18] A. Sen, H. Shah, J. Lemos, and S. Bhattacharjee, "An Algorithm to Extract Handwriting Feature for Personality Analysis", in Proceedings of International Conference on Wireless Communication, 2018, pp. 323-329, doi: 10.1007/978-981-10-8339-6_35.

[19] V. Bhade and T. Baraskar, "A model for determining personality by analyzing off-line handwriting", in Advances in Intelligent Systems and Computing, vol. 705, pp. 345-354, 2018, doi: 10.1007/978-981-10-8569-7_35.

[20] W. Wijaya, H. Tolle, and F. Utaminingrum, "Personality Analysis through Handwriting Detection Using Android Based Mobile Device", J. Inf. Technol. Comput. Sci., vol. 2, no. 2, pp. 114-128, 2018, doi: 10.25126/jitecs.20172237.

[21] S. Asra and S. D.C, "Human Behavior Recognition based on Handwritten Cursives by SVM Classifier", in 2017 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEEECCOT) Human, 2017, pp. 260-268, doi: 10.1109/-ICEECCOT.2017.8284679.

[22] S. Asra and S. D.C, "Personality Trait Identification Using Unconstrained Cursive and Mood Invariant Handwritten Text," Int. J. Educ. Manag. Eng., vol. 5, no. 5, pp. 20-31, 2015, doi: 10.5815/ijeme.2015.05.03.

[23] S. Nag, P. Shivakumara, Y. Wu, U. Pal, and T. Lu, "New COLD feature based handwriting analysis for ethnicity/nationality identification," Proc. Int. Conf. Front. Handwrit. Recognition, ICFHR, vol. 2018-Augus, 2018, pp. 523-527. doi: 10.1109/ICFHR-2018.2018.00097

[24] N. Lemos, K. Shah, R. Rade, and D. Shah, "Personality Prediction based on Handwriting using Machine Learning," in International Conference on Computational Techniques, Electronics and Mechanical Systems, 2018, pp. 110-113, doi: 10.1109/CTEMS.2018.8769221.

[25] J. E. Valdez-Rodríguez, H. Calvo, and E. M. Felipe-Riveron, "Handwritten Texts for Personality Identification Using Convolutional Neural Networks," in Int. Conf. on Pattern Recognition, 2019, pp. 140-145, doi: 10.1007/978-3-030-05792-3_13.

[26] M. A Shaikh, T. Duan, M. Chauhan, and S. N. Srihari. "Attention based Writer Independent Verification", 17th International Conference on Frontiers in Handwriting Recognition (ICFHR), 2020, doi: 10.1109/ICFHR2020.-2020.00074

[27] M. Chauhan, M.A. Hashemi, and S. Srihari. "Explanation based Handwriting Verification ". BMVC 2019: Workshop on Interpretable and Explainable Machine Vision. 2019. doi: 10.48550/ARXIV.1909.02548