Automatic Personality Prediction using Deep Learning Based on Social Media Profile Picture and Posts

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***Abstract*—Uploaded contents by social media users are affected by their personality, for example the profile photo they used and the posts they published. In this research, we create an automatic prediction for Twitter users' personalities through their photo profile and their tweets, comparing the result from using either of the feature and both of them. 1290 Twitter users that had taken MBTI test from 16personalities were used as the dataset. Facial feature from profile photo is obtained by using the face detection model that is combined with smile detection such that not only can we obtain the feature of the face, but also their expressions. As for the color, the feature is obtained by their color composition, which is hue, saturation, and value. For tweets, features are obtained by using a pre-trained word vector. Our result shows that image features can predict personality better than text feature and the combination of text and image features. Based on our result, we also found that a single profile picture is capable of reliably predicting personality.**

***Index Terms*—expression, personality prediction, smile detection, Twitter, word vector**

I. Introduction

Personality is closely related to an individual, which made one individual unique to the others. The need-to-know self-concept based on three aspects: curiosity to learn about themselves, needs to improve, and needs to confirm themselves [1]. Self-concept means to know which things are suitable for them and which are not. Motivation to find another individual compatible with their personality caused them to share information related to their identity more openly. For example, a recent trend of user sharing their personality test result, such as the dichotomy test [2] and Forest MT Seekrtech [3], emerged.

In face-to-face conditions, personality related cues came from their linguistic style, fashion, and gesture. Those styles are projected through visual and textual contents on social media [4]. This may sparks issue of altering such contents to fit the user's desired personality. However, research conducted on American Facebook users shown that the contents they uploaded tends to be strongly related to their personality rather than their "idealized" self [5]. It is possible that such "idealized" self is caused by halo effect, due to the nature of users making their profile picture to match their personal taste [6]. However, as the line of anonymity becomes thicker, online interaction with other users will enable them to express their true self [7]. Moreover, user personality can be tracked through their other footprints. For example, Narcissistic user tend to be more active in social media, but low in confidence.

Personality is relevant to many types of interactions; it has been shown to be useful in predicting job satisfaction, professional and romantic relationship success, and even preference for different interfaces [8]. Personality can also be used in the recommendation system in social media advertisements [9]. Personality and social skills also reflect interactive and important relationships with job performance [10]. The overwhelming usability of personality prediction, combined with huge amount of social media user base, allows automatic personality prediction to be helpful to provide accurate profiling that will be useful to everyone.

Manually evaluating personality test on a large amount can be exhausting. Computer-based personality prediction has been proven to be able to outperform human prediction [11] [12]. This research will attempt to improve past attempt on computer-based personality prediction on Twitter users by using their tweets and profile pictures, making it easy and reliable to be used in the industry and eliminating the need of user taking questionnaires and evaluator to assess the result.

II. Algorithm Analysis

A. Myers Briggs Type Indicator (MBTI)

Myers-Briggs Type Indicator (MBTI) is the most common personality inventory used around the world. Created by Katherine Cook Briggs and Isabel Briggs Myers based on Carl Jung's theory of personality, this personality inventory consists of fouer main categories with two traits each, displayed as the initial of each fitting trait from each category. Those categories can be seen in Table I.

16Personalities adapts this theory and expands it to include a new category called identity. It consists of assertive (A) and turbulent (T). This category relates to how confident some user are about their ability and decisions.

TABLE I
MBTI Categories and Their Descriptions

Categories	Description
Extroversion (E) / Introversion (I)	Relates to interaction with the environment
Sensing (S) / Intuition (N)	Relates to information processing
Thinking (T) / Feeling (F)	Relates to decision making
Judging (J) / Perceiving (P)	Relates to self-management

B. Related Works

Most research in personality prediction uses either one of these two personality model: MBTI [13] [14] and Big Five [8] [15]. Although studies argued that Big Five model suits better for research due to its scientific nature, MBTI has found its way to industry and self-discovery [14], meaning it has larger audience. Computational personality recognition is limited by the availability of labeled data, which is expensive to annotate and often hard to obtain [13]. The amount of self-reported data of personality assessment using MBTI personality traits makes it more preferable to be used in personality prediction research. MBTI traits are also strongly related to Big Five traits, with neuroticism being the exception [5]. Moreover, study by [16] shown that although Big Five allows better personality understanding, MBTI allows for better prediction performance.

Visual features from a photo correlate with user personality [4]. [17] worked with personality prediction using Twitter user's profile picture data, using the Big Five personality model to assign each user score for personality. Their research addressed that every personality trait has its specific type of picture posting. They also reported that extraverts and agreeable user tend to post more colorful pictures, even though the pictures are not aesthetically pleasing.

Facial expression is positively correlated to smiling, joy, and positive emotion on conscientiousness while negatively correlated to negative emotion. [17] reported that openness and extraversion have the most correlations with color features. Openness was found to correlate with more green tones, lower in brightness, and higher in saturation. Meanwhile, extraversion correlates with blue and green tones, lower in brightness, and a mix of saturated and unsaturated colors.

Image features for depression and anxiety detection was done by [18]. Grayscale color space has been reported to be used often by both depressed and anxious twitter user. Depressed user also tends to have a profile picture consisting of a single person with less facial expression as to prevent showing any negative emotion. Anxious user, however, tends to have smiling profile picture. The lack of aesthetic cohesion also prominent across both depressed and anxious user.

Personality prediction on Instagram through visual contents was done by [19] using Big Five for the personality model. Two features, namely visual and content features, were used to analyze personality from Instagram posts. For visual features, Hue-Saturation-Value (HSV) color space and Pleasure-Arousal-Dominance (PAD) was used, whereas for content features objects in the picture were analyzed and used through the use of Google Vision API tagger, clustering them into 17 main categories. Amount of faces and people in the picture were also used for content features. The results show that both feature by themselves improves the prediction ability, but combining the features does not yield any improvement.

Research for tweet-based prediction was done previously by [13], focusing on a large-scale dataset, utilizing gender and word n-grams ($n = 1, 2, 3$) as the main features, and using logistic regression as the classifier. This dataset was gathered from self-reported tweets of the users' MBTI types of personality assessment. They gathered 1,500 distinct users with the final corpus of 1.2 million tweets. Their prediction shows significant improvement in predicting E-I and T-F categories as the number of tweets used in the learning process increased. S-N and J-P prediction does not show any improvement. This research also shows that gender has a strong correlation with the T-F category, but not on E-I. They found out that the correlation between $Thinking$ and gender=men is 0.57, while it is 0.27 in the gender-controlled experiment. On the other hand, correlation of $Feeling$ with gender=female is 0.78 and 0.54 for gender-controlled experiment.

N-gram model has been used as a language model by grouping words into classes [20]. It is done by checking the word neighbors in previous occurrences along with their part-of-speech tags (POS). By this means, n-grams behavior is syntactic rather than semantic. To solve this problem we are going to use FastText model [21]) which is based on continuous bag-of-words (CBOW) architecture. The CBOW model predicts the source word according to its context. This approach gives more semantic behavior that will help in text classification for our proposed personality prediction model.

C. Datasets

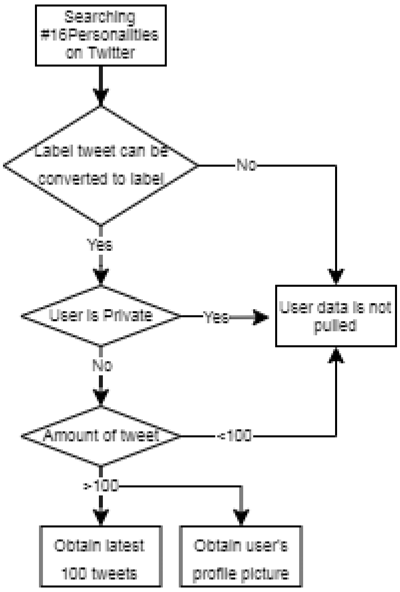

Fig. 1. Flow of Data Pulling

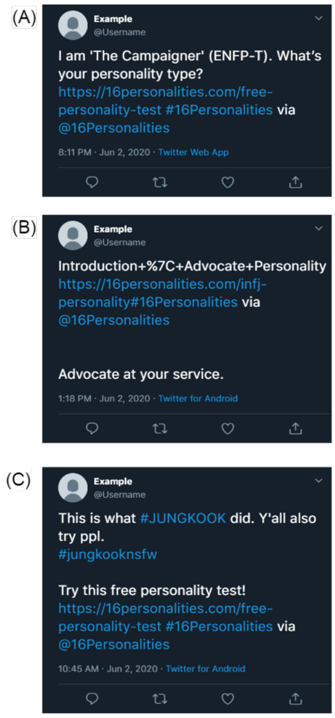

Fig. 2. Example of tweets used for label, notice that both on (A) and (B) has the keyword needed, while (C) does not.

1) Obtaining the Dataset: The dataset is obtained from Twitter who shared their self-assessed MBTI result from 16personalities. The entire data pulling scheme can be seen in Fig. 1 . For each user obtained, we also retrieve their latest 100 tweets from their timeline and their profile picture. The tweet can be found by searching #16personalities, with examples on Fig. 2. The picture does not have to have a human face in it as profile pictures are pictures that have been chosen to represent the users themselves in Twitter [10]. Users with closed account (private account) are exempted from the pulling process as not only they are inaccessible, closed/open account does not affect the personality of the user [22]. After processing the label which will be explained in the next subchapter, we obtained 1,290 users.

2) Dataset Labels: There are 16 different types of personality as seen in Table II. They consist of 4 categories which are Extraversion/Introversion, Sensing/Intuition, Thinking/Feeling, and Judging/Perceiving. Table III shows the amount of each category. Tweet used to obtain the user is used to determine the label. In this case, we look for two possible keywords: the initials or the type based on 16 personalities. For this experiment, we disregard the identity category provided by 16 personalities because MBTI does not have this category. Given the tweet has the keyword required, it will be used immediately as the label, separated for each category. The variation of labels can be seen on Table II and the amount of each category can be seen on Table III.

3) Smile Detection Dataset: GENKI-4K is a dataset [23] containing faces spanning a wide range of illumination conditions, geographical locations, personal identity, and ethnicity. From 4000 labelled faciall images, 2162 images are labelled as "smile" and 1828 images are labelled as "nonsmile".

TABLE II
16PERSONALITIES TYPES AND THEIR CORRESPONDING MBTI INITIALS

Architect (INTJ)	Logician (INTP)	Commander (ENTJ)	Debater (ENTP)
Advocate (INFJ)	Mediator (INFP)	Protagonists (ENFJ)	Campaigner (ENFP)
Logistician (ISTJ)	Defender (ISFJ)	Executive (ESTJ)	Consul (ESFJ)
Virtuoso (ISTP)	Adventurer (ISFP)	Entrepreneur (ESTP)	Entertainer (ESFP)

TABLE III
USER AMOUNT FOR EACH CATEGORY

Categories	Amount
Extroversion (E)	390 (30%)
Introversion (I)	**900 (70%)**
Sensing (S)	**958 (74%)**
Intuition (N)	332 (26%)
Thinking (T)	301 (23%)
Feeling (F)	**989 (77%)**
Judging (J)	**710 (55%)**
Perceiving (P)	580 (45%)

III. Methods

A. Smile Detection

We used face alignment [24] to the GENKI-4K data set to add robustness to rotations and translations of the classification model. Before doing the alignment process, we used landmark localization to get two landmarks positions which are the left corner of the left eye and the right corner of the right eye. Then, by using the corresponding landmarks we can do an eye-based face alignment method to fix the eyes positions. We are using the affine transform matrix which consists of rotation and scaling increases the base drag but reduced the projectile wave drag with a resultant decrease of the total drag.

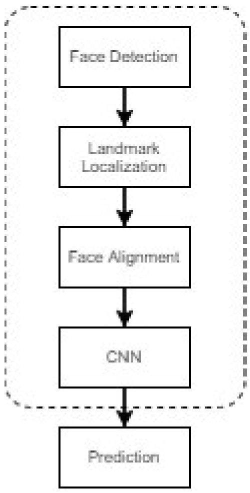

Fig. 3. Flow of Smile Detection.

Furthermore, a convolutional neural network (CNN) [25] is used to train on the data so it can know whether a picture has a smiling face or not. We compare our approach with [25] approach with the same data set, increasing the image input size from 32×32 to 120×120. We used 3 convolution layers each with leaky ReLU as activation function followed by pooling layer and dropout (0.5) layer then connected by 1 fully connected layer with sigmoid as the activation function. The result is reported in terms of average accuracy over four rounds of cross-validation.

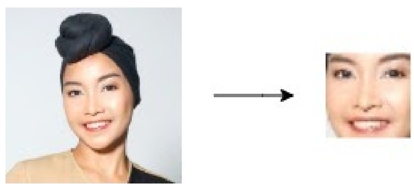

Fig. 4. Example of an aligned face using eye-based alignment.

We used leaky ReLU instead of ReLU because ReLU only gave us 92.94% accuracy, whereas leaky ReLU gave higher accuracy as seen in Table IV. Our proposed approach outperformed [25] by 0.76%. We suspect this difference was made by input image size. One room for improvement is to improve face alignment used before proceeding to CNN as there were still faces that were not aligned properly, affecting the performance of the network.

TABLE IV
Comparison of methods on the GENKI-4K database

Method	Accuracy (%)
[25]	93.35
Proposed	**94.11**

B. Color Feature

Hue-Saturation-Value (HSV) [17] is used due to its ability to mimic how the human visual system organizes colors [26]. The HSV is divided into three parameters.

1) Hue: As proposed in [17], the hue parameter is divided into six categories: red, orange, yellow, green, blue, and violet. The value of each category is calculated by counting every pixel that falls into the corresponding category then by the total pixels of the picture.

2) Saturation: For saturation, we calculate the pixels that fall into each category. The categories are low, mid, and high saturation. We divide three categories intervals equally, divided by the total pixel of the image.

3) Value: Value is calculated by counting all pixels that fall into each category (low, mid, and high value). The three categories are divided equally, divided by the total pixel of the image.

C. Text Processing

Text pre-processing is done to all tweet except the label tweet, as it is solely used to obtain the label. Given that some of the tweet is not in English, which is detected by Twitter API, the tweet is translated using Google Translate from source language to English. Later processing is done systematically as follows.

- Link removal. Since a link does not possess any information, deletion is necessary.
- Emoji removal. We attempt to focus on linguistic features; therefore, we remove emoji.
- Hashtag and mention removal. Hashtag contains information that is too specific for a period of time rather than reflecting the actual personality of a user, and mention does not possess any meaning. Both of them are removed.
- Number and symbol removal. Since words that contain numbers and symbols (such as $,%, ? &, , etc.) are removed, we can safely remove both of them.
- Case folding. All characters are converted to lowercase for an easier process in the later steps.
- Word tokenization. Sentences are broken into words.
- Stemming. Affix accommodates syntactic while only alter semantic feature for a slight, so we decided to use the root word instead.
- Stop word removal. Common words that are used often do not represent a class clearly.

Processed tweets are then converted to vectors using a pretrained FastText model [21] on a 300-dimension word vector.

D. Model Creation

We train our dataset on three different models: linguistic features (Fig. 5) visual features (Fig. 6), and both features (Fig. 7). We train our dataset per category, as we find that multiclass learning drops the performance significantly and consumes more time to process. We randomly split the dataset into 3 parts: 64% for training, 16% for validation, and 20% for testing.

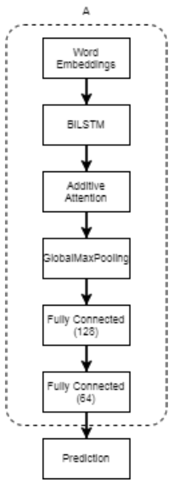

Fig. 5. Model for text posts.

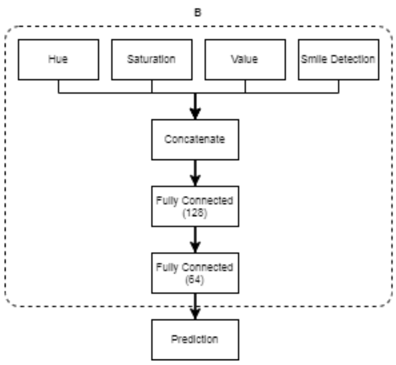

Fig. 6. Model for profile picture.

IV. Result and Discussion

TABLE V
COMPARISON OF RESULTS BETWEEN MODELS

Model	Train F1	Validation F1	Test F1
Tweet	0.7514	0.6655	0.6689
Picture	**0.8536**	**0.8101**	**0.7579**
Picture + Tweet	0.7688	0.6959	0.6637

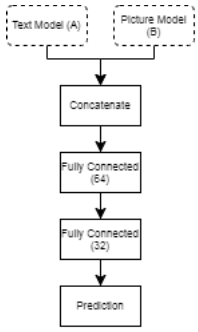

Fig. 7. Model for both text and profile picture.

From Table V we observed that the picture model yields consistently the best result, while the linguistic model yields the worst. We assume that data translation heavily affects the diction, resulting in lower results. While the model of combined picture and tweet yields results not far from the tweet model, we suspect the low prediction power of the linguistic model hinders the performance of the picture model when combined. The lower performance of the feature combination might also indicate that picture and text feature do not correlate well.

TABLE VI
ACCURACY COMPARISON BETWEEN MODELS IN 4 CATEGORIES

Model	E-I	S-N	T-F	J-P
Baseline	0.7	0.74	0.77	0.55
Tweet	0.667	0.703	0.732	0.541
Picture	**0.733**	**0.785**	**0.814**	**0.626**
Picture + Tweet	0.701	0.761	0.791	0.554
[13]	0.725	0.774	0.612	0.554

Table VI shows that our picture model performs better than the other models in terms of accuracy. Between our picture model and the [13], we can see huge improvements for T-F category and a big improvement for J-P category. Although, there is no significant improvement for E-I and S-N categories. From this result, we can expect that picture features are better for predicting T-F and J-P categories than text features. [13] also stated that J-P category is difficult to learn which makes our improvement in J-P category are quite significant. Our text model shows a worse performance in accuracy compared to [13] possibly because of the number of tweets used per user in training process which is only 100 tweets/user. They found on their research that for T-F category the training process converges at 500 tweets/user and it still improves even after 2000 tweets/user for E-I category. Having the information that our picture model yields the best result in predicting personality than the other two models, we are trying to see the correlation between picture features with each category.

Table VII shows the correlation between image features with each MBTI categories. These category pairs are made based on our model so that negative correlation indicates a correlation with the first label of the pair and positive correlation shows a correlation with the second label. Although, this is not the

TABLE VII
PROPOSED PICTURE MODEL FEATURES CORRELATION WITH MBTI CATEGORIES IN PEARSON CORRELATION

Feature	E-I	S-N	T-F	J-P
Hue	0.05	-0.08	0.05	0.05
Saturation	0.33	-0.17	-0.2	-0.12
Value	0.04	0.1	-0.31	0.16
Smile	0.22	0.04	-0.13	0.14

case for the combination of all features. The correlation score for the combination of all features shows how well the features correlates each category and not the labels.

E-I category positively correlates with saturation and smile feature. This result shows that a higher mean in saturation strongly correlates to user with introversion trait. User with higher introversion trait tends to have a profile picture with higher saturation mean. It is also interesting that we found that the smile feature correlates with introversion trait rather than extraversion, which means user with introversion trait are more likely to have a smiling face in their profile picture.

For the S-N category, our result shows that it positively correlates with value and negatively correlates with saturation. User with intuition trait tends to have lower saturation mean profile pictures and user with sensing trait tends to have higher saturation mean profile picture. User with intuition trait was found to correlate with the value which means their picture emphasizes higher brightness.

Category T-F is negatively correlated with saturation, value, and smile features. This indicates user with feeling trait tends to show saturated pictures, picture with lower brightness average, and face that is not smiling. It is the other way around for user with thinking trait.

J-P category positively correlated value and smile features and negatively correlated with saturation. User with perceiving trait tends to have a picture with higher brightness and smiling face if there is a face in the picture. The result also shows that user with the perceiving trait are more likely to have saturated pictures.

From Table VII, we can see that from 4 picture features hue has the lowest correlation with every category. It shows that standalone hue does not perform really well in predicting personality. Meanwhile, the combination of all features shows a significant performance with the lowest r = 0.255 for predicting the S-N category. This result also shows that image features strongly correlate with E-I and T-F categories.

Based on the picture model result in both F1 and accuracy, we have shown that our model is capable of predicting personality traits. Although J-P category prediction performs the weakest, on the dataset this category is the balanced one. This allows a personality assessment with only a profile picture as the source to predict personality. It opens for possibilities that requires personality assessment with less resources needed.

V. CONCLUSION

In this paper, we attempt to predict personality using profile pictures and/or tweets using deep learning from Twitter users. We gathered the users' personalities from shared self-assessed MBTI results from 16Personalities. For the text feature, we focused on tweets in the English language despite the need to use translated tweets to increase the amount of data.

We compared the performance between picture features, text features, and the combination of both. From the result we discovered that picture features perform best. We have also found that hue does not perform really well in predicting personality.

The model with the text feature performs worse than our picture model. We assume that the translated tweets and the limitation on the text amount of data are affecting the performance. While the text model performance also affects the combined features model, we also assume that text and picture features do not correlate well as there are no significant improvements from the text model result.

We acknowledge that our research has a limitation on the amount of data used. Although the result yields quite a reasonable result, we would like to see further improvement in this research by expanding the feature and the amount of dataset on both pictures and tweets.

REFERENCES

[1] B. B. Lahey, *Psychology: an introduction*, 11th ed. New York: McGraw-Hill Higher Education, 2012.

[2] F. H. Pridianto, "Dichotomy Test, Tes Kepribadian yang Viral di Media Sosial, Silahkan Coba dan Lihat Hasilnya." [Online]. Available: https://suryamalang.tribunnews.com/2018/12/06/dichotomy-test-tes-kepribadian-yang-viral-di-media-sosial-silahkan-coba-dan-lihat-hasilnya

[3] D. V. Putsanra, "Forest MT Seekrtech yang Viral & Mengapa Orang Suka Tes Kepribadian." [Online]. Available: https://tirto.id/forest-mt-seekrtech-yang-viral-mengapa-orang-suka-tes-kepribadian-elEn

[4] L. P. Naumann, S. Vazire, P. J. Rentfrow, and S. D. Gosling, "Personality Judgments Based on Physical Appearance," *Pers Soc Psychol Bull*, vol. 35, no. 12, pp. 1661–1671, Dec. 2009. [Online]. Available: http://journals.sagepub.com/doi/10.1177/0146167209346309

[5] A. Furnham, "The big five versus the big four: the relationship between the Myers-Briggs Type Indicator (MBTI) and NEO-PI five factor model of personality," *Personality and Individual Differences*, vol. 21, no. 2, pp. 303–307, Aug. 1996. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0191886996000335

[6] E. Harris and A. C. Bardey, "Do Instagram Profiles Accurately Portray Personality? An Investigation Into Idealized Online Self-Presentation," *Front. Psychol.*, vol. 10, p. 871, Apr. 2019. [Online]. Available: https://www.frontiersin.org/article/10.3389/fpsyg.2019.00871/full

[7] J. A. Bargh, K. Y. A. McKenna, and G. M. Fitzsimons, "Can You See the Real Me? Activation and Expression of the "True Self" on the Internet," *J Social Isssues*, vol. 58, no. 1, pp. 33–48, Jan. 2002. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1111/1540-4560.00247

[8] J. Golbeck, C. Robles, M. Edmondson, and K. Turner, "Predicting Personality from Twitter," in *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing*, Oct. 2011, pp. 149–156.

[9] S. C. Matz, M. Kosinski, G. Nave, and D. J. Stillwell, "Psychological targeting as an effective approach to digital mass persuasion," *Proc Natl Acad Sci USA*, vol. 114, no. 48, pp. 12 714–12 719, Nov. 2017. [Online]. Available: http://www.pnas.org/lookup/doi/10.1073/pnas.1710966114

[10] W. Bleidorn and C. J. Hopwood, "Using Machine Learning to Advance Personality Assessment and Theory," *Pers Soc Psychol Rev*, vol. 23, no. 2, pp. 190–203, May 2019. [Online]. Available: http://journals.sagepub.com/doi/10.1177/1088868318772990

[11] W. Youyou, M. Kosinski, and D. Stillwell, "Computer-based personality judgments are more accurate than those made by humans," *Proc Natl Acad Sci USA*, vol. 112, no. 4, pp. 1036–1040, Jan. 2015. [Online]. Available: http://www.pnas.org/lookup/doi/10.1073/pnas.1418680112

[12] J. Hinds and A. Joinson, "Human and Computer Personality Prediction From Digital Footprints," *Curr Dir Psychol Sci*, vol. 28, no. 2, pp. 204–211, Apr. 2019. [Online]. Available: http://journals.sagepub.com/doi/10.1177/0963721419827849
[13] B. Plank and D. Hovy, "Personality Traits on Twitter—or—How to Get 1,500 Personality Tests in a Week," in *Proceedings of the 6th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*. Lisboa, Portugal: Association for Computational Linguistics, 2015, pp. 92–98. [Online]. Available: http://aclweb.org/anthology/W15-2913
[14] M. Gjurković and J. Šnajder, "Reddit: A Gold Mine for Personality Prediction," in *Proceedings of the Second Workshop on Computational Modeling of People's Opinions, Personality, and Emotions in Social Media*. New Orleans, Louisiana, USA: Association for Computational Linguistics, 2018, pp. 87–97. [Online]. Available: http://aclweb.org/anthology/W18-1112
[15] L. Liu, D. Preotiuc-Pietro, Z. R. Samani, M. E. Moghaddam, and L. Ungar, "Analyzing Personality through Social Media Profile Picture Choice," *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 10, no. 1, pp. 211–220, 2016, number: 1. [Online]. Available: https://ojs.aaai.org/index.php/ICWSM/article/view/14738
[16] F. Celli and B. Lepri, "Is Big Five better than MBTI?" in *Proceedings of the Fifth Italian Conference on Computational Linguistics CLiC-it 2018*, E. Cabrio, A. Mazzei, and F. Tamburini, Eds. Accademia University Press, 2018, pp. 93–98. [Online]. Available: http://books.openedition.org/aaccademia/3147
[17] B. Ferwerda, M. Schedl, and M. Tkalcic, "Using Instagram Picture Features to Predict Users' Personality," in *MultiMedia Modeling*, ser. Lecture Notes in Computer Science, Q. Tian, N. Sebe, G.-J. Qi, B. Huet, R. Hong, and X. Liu, Eds. Cham: Springer International Publishing, 2016, pp. 850–861.
[18] S. Chandra Guntuku, D. Preotiuc-Pietro, J. C. Eichstaedt, and L. H. Ungar, "What Twitter Profile and Posted Images Reveal about Depression and Anxiety," *ICWSM*, vol. 13, no. 01, pp. 236–246, Jul. 2019, section: Full Papers. [Online]. Available: https://ojs.aaai.org/index.php/ICWSM/article/view/3225
[19] B. Ferwerda and M. Tkalcic, "Predicting Users' Personality from Instagram Pictures: Using Visual and/or Content Features?" in *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*. Singapore Singapore: ACM, Jul. 2018, pp. 157–161. [Online]. Available: https://dl.acm.org/doi/10.1145/3209219.3209248
[20] P. F. Brown, V. J. Della Pietra, P. V. deSouza, J. C. Lai, and R. L. Mercer, "Class-Based *n*-gram Models of Natural Language," *Computational Linguistics*, vol. 18, no. 4, pp. 467–480, 1992. [Online]. Available: https://aclanthology.org/J92-4003
[21] T. Mikolov, E. Grave, P. Bojanowski, C. Puhrsch, and A. Joulin, "Advances in Pre-Training Distributed Word Representations," *arXiv:1712.09405 [cs]*, Dec. 2017, arXiv: 1712.09405. [Online]. Available: http://arxiv.org/abs/1712.09405
[22] D. Azucar, D. Marengo, and M. Settanni, "Predicting the Big 5 personality traits from digital footprints on social media: A meta-analysis," *Personality and Individual Differences*, vol. 124, pp. 150–159, Apr. 2018. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0191886917307328
[23] http://mplab.ucsd.edu, "The MPLab GENKI Database, GENKI-4K Subset."
[24] A. Asthana, S. Zafeiriou, S. Cheng, and M. Pantic, "Incremental Face Alignment in the Wild," in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Jun. 2014, pp. 1859–1866, iSSN: 1063-6919.
[25] S. Bianco, L. Celona, and R. Schettini, "Robust smile detection using convolutional neural networks," *J. Electron. Imaging*, vol. 25, no. 6, p. 063002, Nov. 2016.
[26] M. Tkalcic and J. Tasic, "Colour spaces: perceptual, historical and applicational background," in *The IEEE Region 8 EUROCON 2003. Computer as a Tool.*, vol. 1, Sep. 2003, pp. 304–308 vol.1.