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Research Article

An Adaptive Bacterial Foraging Algorithm Based Faster Region–CNN for Classifying Personality Traits

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ABSTRACT

Mechanized personality discovery from image features has arisen and acquired a lot of consideration in the branch of knowledge of full of feeling registering and opinion examination. This work presents a deep learning model that can measure personality characteristics on five classes which is Conscientiousness (CON), Openness to experience (OPN), Extraversion (EXT), Neuroticism (NEU) and Agreeableness (AGR) from a picture. This work proposes a model utilizing Convolutional Neural Networks to naturally extract highlights from a representation that are marks of personality qualities. To improve the detection level of personality Traits, Faster Region Convolutional Neural Network (F-CNN) model with Adaptive Bacterial Foraging Optimization (ABFO) is presented. The proposed model exhibits the effectiveness of the acquainted technique with a promising personality forecast model and can group the client's personality qualities when contrasted with the best-in-class procedures. While assessing the proposed technique, results show a ruthless and critical exactness improvement in contrast with the latest outcomes for the Personality dataset for personality recognition. Moreover, present the usually utilized datasets and call attention to a portion of the difficulties of personality-mindful proposal frameworks.

Keywords: Personality computing, Deep-learning (DL), Personality traits, convolutional neural network, Optimization.

INTRODUCTION

Social Networking Sites (SNS) continue to have an impact on people's day-to-day lives and have evolved into an essential social platform for social interaction [1]. Interview systems for recruitment, counselling systems, product recommending systems, personal recommendation systems, and credit scoring systems are some applications that could benefit from user personality data [2]. Researchers in the Natural Language Processing (NLP) community is increasingly interested in the topic of automatic personality prediction [3].The My Personality dataset contains these features. However, there are differences between the studies [26] that used a dictionary called Structured Programming for Linguistic Cue Extraction (SPLICE) to extract features [4]. In the fields of AI and pattern recognition, automatic personality prediction is a relatively recent and highly active area of research. To identify a face region from a picture, various strategies, for example, the basic projection technique [5] is proposed. Because it is nearly invariant against changes in the size and orientation of the face, color-based segmentation is used more frequently than other approaches in face detection [6].A new kind of recommendation system that uses the personality trait of the user to make better recommendations had come into existence. Personality-aware recommendation systems are the name given to this category of systems [7].The issue with conventional recommendation systems has been successfully addressed by this new type of recommendation system [8].

The only difference between personality-aware recommendation systems and conventional recommendation systems is that personality information about the user is included in the recommendation process [9,10]. The advancement of deep neural networks(DNN) has demonstrated remarkable performance in a variety of NLP tasks, like sentiment analysis and opinion mining [11,12].It is important to note that personality recognition and NLP applications are very similar because they both focus on mining the attributes of users from images. Method for personality recognition based on DL that tries to use both the AdaBoost algorithm and the Convolutional Neural Network (CNN) [13] , even though CNN has been used successfully for a variety of NLP tasks and has the potential to extract local features, using different filter lengths may hurt the CNN classifier's effectiveness [14]. Furthermore, the lack of a large enough dataset, particularly when employing a DL algorithm, is a major impediment to optimizing model performance [15].

Contribution of this work is as follows:

For classification of personality traits, An ABFO Based FCNN model is presented. Using FCNN model, features are extracted from the particular region (i.e., human face). Then these features are given as input to the classification model. In the approach, fully connected layer with ABFO is presented as classifier to classify the personality traits. To enhance the convergence ability of BFO, Chaotic Sequence Based on Tent Map is presented.

LITERATURE REVIEW

Lorem framework based on Machine learning(ML) algorithms provide the foundation for the prediction of personality. Three machine learning algorithms specifically, Stochastic Gradient Descent (SGD) as well as two troupe learning algorithms, Gradient Boosting (XGBoost) and stacking were used in this review by Adi, G. Y. N. N. et al. in 2018[16]. Twitter and its usage are as an asset for some kinds of examination. A few past examinations have endeavoured to naturally foresee clients' personalities. Notwithstanding, a couple of them have done all necessary investigations for Bahasa Indonesia data. In order to categorise eight key personality qualities, Hussain Ahmad et al. (2021) suggested a deep learning model that combines CNN and Long Short-Term Memory (LSTM). The model's efficacy in correctly classifying personality traits was demonstrated by their trials on a benchmark dataset, which showed better performance when compared to state-of-the-art techniques. At long last, we assess the adequacy of our approach through measurable investigation. With the knowledge acquired from this exploration, associations are fit for pursuing their choices regarding the enlistment of personnel proficiently.

Kamal El-Demerdash et al in 2022 [18] presented the model to gets benefit from, moving learning in regular language handling through driving pre-prepared language models specifically Elmo, ULMFiT, and BERT. The proposed work shows the capability of the acquainted strategy to be a promising model for personality detection. While assessing the proposed strategy, results show a cutthroat and huge exactness improvement of around 1.25% and 3.12% in contrast with the latest outcomes for the two best quality level Expositions and my Personality datasets for personality detection. One of the most appealing games is the First Person Shooter (FPS) genre, making it an ideal setting for assessing a player's personality, emotions, and interests. in 2022 [19] by Muhannad Quwaider et al. The purpose of the game's distribution in the Google Play Store was to collect custom data from customers in unsupervised circumstances. The Five-Factor Model (FFM), one of the most well-known models in this field, was used to collect the data for personality traits. Using our distributed game, we were able to collect thousands of real-world customer data. The motivation for personality prediction and classification then came from novel machine learning methods.

Kunal Biswas et al. [20] presented a method in 2021 that builds a vocabulary by text detection, identification, and image annotation using banners, descriptions, and profile photos. In order to create a feature framework that can be fed into a fully connected neural network for classification, they devised a fusion technique based on evolutionary algorithms. M. Jansi Rani et al. [21] presented a reliable technique in 2021 for drawing insights from microarray-based gene expression datasets, which are difficult to extract because they usually have a lot of genes but few samples. To find the most important and instructive genes with the most changes, they used a gene selection procedure. Their method used the Bacterial Foraging Optimisation (BFO) strategy for gene selection and used data mining techniques to classify microarray data and discover genes controlled differentially by different disorders.

A hypothesis is that clients with comparable personalities are supposed to show shared standards of conduct while collaborating through informal communities. With the objective of personality acknowledgment as far as examining client action inside Facebook, they gathered data of personality traits of clients and their profiles on Facebook, thus prospered an application utilizing the Programming interface Facebook by Souri, A., et al in 2018 [22]. Five classifiers, one for each of the Enormous Five model's characteristics, were used in the personality prediction framework. Nevertheless, this review introduced the model by combining a statistically based image feature with a predefined model feature to enhance personality prediction performance [27]. Proposed model, the boosting-choice tree, was more accurate than previous tests that had the option to foresee personality based on the factors in their profiles in five factors for including it as a model for perceiving personality when looking at the results of classifiers. Optimized machine learning models using bio-inspired algorithms have also been used to enhance feature selection and classification accuracy [29].An emotion recognizer using deep learning, combining an improved Faster R-CNN face detector with transfer learning in NasNet-Large CNN [30] and BERT word embedding with convolutional networks [31] to assess personality mapping, paving ways for smarter contextualization that can further be applied to areas like forensics, recruitment, and mental health.

To achieve feature selection a new method called IDGWOFS [32] were proposed where Gaussian Chaos Map is applied by a novel improved distributed GWO with symmetric uncertainty. In another work [33] Chimp Optimization Algorithm is applied to tune the CNN based model for skin detection, performing directly over RGB and HVS color spaces. Results indicate that chimp algorithm substantially improves CNN performance, rendering it an appealing strategy for skin classification endeavours. Big Five personality traits and the NRC Emotion Lexicon scope can be used to extract emotional nuances. This research [34] integrates and evaluates three strategies to determine the most successful technique for extracting the personality traits. Fusion approaches like additive attention-based fusion emphasize the importance of each modality on a multimodal scheme [35] based on facial action units and speech features for explainable personality and interview-trait predictions.

METHODOLOGY OF PROPOSED FCNN-ABFO PERSONALITY TRAITS CLASSIFIER

This research work classify Personality Traits From various features like emotion and facial expressions, our proposed work is graphically represented in Figure 1.These image frames from the video would be extracted based on the key-frame selection technique. Further, this rich set of labeled images would be used for the identification of personality traits based on non-verbal cues and image augmentation tools may be used to enhance the training dataset. Using Faster Region–CNN model, features are extracted from the particular region (i.e., human face). Then these extracted features are given as input to the classification model. In the approach, a fully connected layer with an Adaptive Bacterial Foraging Algorithm (ABFA) is presented as a classifier to classify the personality traits, and also the adaptive function considered as the Chaotic Sequence Based on Tent Map is presented.

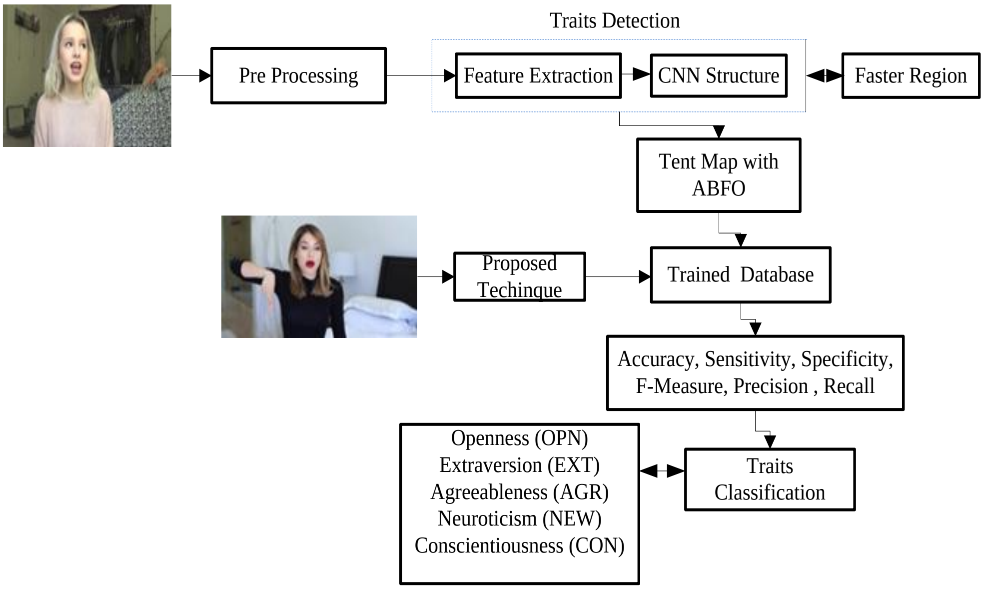

Figure 1. Overview of proposed Faster CNN-ABFO Model

Pre-processing: To further develop image quality and stay away from messy information, information pre-handling changes the first dataset into an accessible and standard dataset before placing the information into model preparation. The primary reason for pre-handling is to amplify the extracted features, thus more contextual features are created, and a standardized information base [23].

Feature Extraction: In this personality detection process, face and emotional features are considered to extract from pre-processed images. Normal feelings, to be specific resentment, dread, expectation, trust, shock, misery, delight, and revulsion and the opinions of every one of these words can be good or pessimistic. The got feature vectors addressing the arrangement of key unique images are encoded into a solitary feature vector utilizing covariance. One-layered convolution utilizes fixed-size convolution organizations to slide over the arrangement and distinguish features in various positions.

Traits Classification: Proposed CNN Classifier: Most of the research works use neural organization designs, such as CNN and region-based frameworks, to create efficient personality prediction frameworks. The DL method has become increasingly popular in recent years. In any case, the multi-model DL design that was presented in this review combined a predefined model feature and a measurable-based facial feature to work on the presentation of foreseeing an individual's personality [24].This study will divide this personality prediction framework into five classes, with each classifier focusing on one of the five major personality traits. A convolutional layer, a pooling layer, and finally completely connected layers make up this CNN structure's three layers. The structure that can be seen in Figure 2 indicates that the most crucial doubt regarding issues that are illuminated by CNN should not have spatially dependent features. Where the layers are, CNN's feature learning and arrangement processes will take place.

Convolutional Layer: The feature depictions of information sources are presented in this layer. In a similar feature map, each neuron removes nearby characteristics of different situations in the previous layer; however, for individual neurons, its extraction is the nearby credits of the same situations in a different feature map.

Pooling Layer: This layer has the impact of secondary feature extraction. It can diminish the estimations of the feature maps and increment the durability of feature extraction. The proportion of feature maps in the pooling layer is settled by the moving development of parts.

Faster Region CNN: In the field of personality discovery using deep learning, the method of the region of interest polling is receiving a lot of attention. Recognition of items from a scene or image containing various items could be an occurrence. The task of looking through the information image to identify areas where there is a likelihood of product area is a very quick one. A region known as the Region of Interest (return on initial capital investment) restricts the areas in which an item is plausible. Our test, on the other hand, focuses on finding a standard for evaluating clients' personalities without requiring them to meet the personality stock. A CNN-generated feature map with multiple convolution layers and max pooling layers.

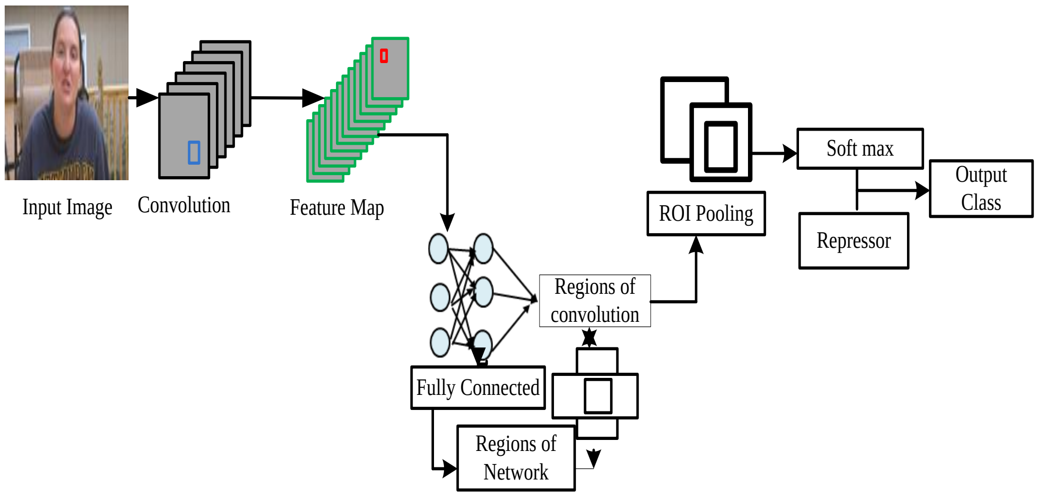

Figure 2. Proposed F-CNN Structure

Subdividing the feature map space into Regions of Interest yields an N*N matrix. N represents the ROI in this instance. The region model is the space that was used to find the Region of Interest. The entire region process space is divided into equal-sized parts using this strategy. The input image is run via a Faster R-CNN to create a convolutional feature map rather than providing region recommendations straight into the CNN. After identifying the suggested locations, the ROI pooling layer turns them into fixed-size squares for additional examination.

Fully Connected layer: They connect each neuron in the current layer to each neuron in the previous layer. This capability is finished in the whole connected layer, which has a different perception. The resulting layer uses fullscale cross-entropy to give the expected error. Regression is typically used for classification assignments because it provides an overall probability conveyance of the results [25].

Bacterial Foraging Optimization: In order to enable autonomous fine-tuning, the backbone network uses Bacterial Foraging Optimisation (BFO) for hyper-parameter optimisation. The method uses flagella to simulate how bacteria move, which enables them to swim effectively. Chemotaxis is the process by which bacteria travel away from hazardous environments and towards nutritional gradients. However, chemotactic growth can be disrupted by abrupt environmental changes or attacks, which can lead to bacteria spreading to new sites or encountering other difficulties. In order to increase BFO performance, the research suggests an adaptive function based on a chaotic map. This program improves information sharing across bacteria by extracting and calculating characteristics in the BFO search process.

RESULTS

Execution of proposed personality traits detection is implemented in python 3.6.4 with text blob, NumPy, matplotlib library with 64-cycle engineering. Our proposed results contrasted with existing indicator and optimization procedures with various performance measures. classifier for every one of the personality factors since it was conceivable that a classifier would answer preferably in one personality figure over different classifiers in another component. This part examined dataset depiction and relative investigation of various classes of personality traits like CON, EXT, AGR, NEW, and OPN to Experience.

Database Description: Chalearn has provided a dataset: "https://chalearnlap.cvc.uab.cat/dataset/24/description" for an apparent personality challenge comprising of 10,000 short video clips with annotations, that make up the initial feelings informational collection CVPR'17 initial feelings dataset. In recordings, individuals exhibit a variety of orientations, ages, identities, and nationalities. Images were extracted from these clips and annotations were average out for the redundant clips. The Five Element Model termed as the Big Five or OCEAN, which is the predominant worldview in personality detection, was used to analyse the traits of the personality.

Figure 3. Sample Images from the Database

The boundaries of confusion metrics for five personality traits, as determined by various classifiers like DNN, CNN, and FCNN, as well as our proposed optimization using a classifier model, are depicted in Table 1. In all metrics and traits, The Proposed model has shown to outperform all other models across all personality traits tolerating closeness to ≥ 90% for all traits. Average performing next best is FCNN at ~87% average accuracy. The precision measure of the accuracy of positive prediction is lowest in DNN (in the 70s), meaning that it had less accurate predictions. The Proposed model scores real positives much better on the recall, with recall around 90% for all traits. FCNN follows closely with an average recall of 87%. DNN has the lowest recall, with values slightly below 73%. The Proposed model shows the highest F-measure values, which indicates a good balance between precision and recall. Its average score is 90.62%. Again the rank of the FCNN is second with the average F–measure of 87.26%. DNN already falls behind in the F-measure score, indicating a weaker overall performance than the other methods.

Table 1. Comparative analysis of Personal traits with Classification

Measure		**OPN**	**EXT**	**NEW**	**AGR**	**CON**	***Avg***
Precision	DNN	72.70	73.79	71.62	71.18	68.56	*71.57*
	CNN	84.53	84.47	84.56	83.93	83.62	*84.22*
	FCNN	86.66	87.66	87.74	86.74	86.72	*87.10*
	Proposed	91.69	91.47	89.79	89.10	90.87	***90.58***

Recall	DNN	71.97	73.79	71.08	73.25	70.61	*72.14*
	CNN	84.38	84.58	83.84	84.84	84.46	*84.42*
	FCNN	87.12	87.66	86.66	87.84	87.84	*87.42*
	Proposed	89.82	90.03	91.12	91.24	91.24	***90.69***
F-Measure	DNN	72.34	73.79	71.35	72.20	69.57	*71.85*
	CNN	84.45	84.52	84.20	84.38	84.03	*84.31*
	FCNN	86.89	87.66	87.20	87.29	87.28	*87.26*
	Proposed	90.74	90.75	90.45	90.15	91.05	***90.62***
Accuracy	DNN	73.03	74.32	73.03	72.93	70.97	*72.85*
	CNN	84.47	84.52	84.27	84.30	83.96	*84.30*
	FCNN	86.86	87.66	87.28	87.21	87.20	*87.24*
	Proposed	90.66	90.64	90.38	90.04	90.04	***90.35***

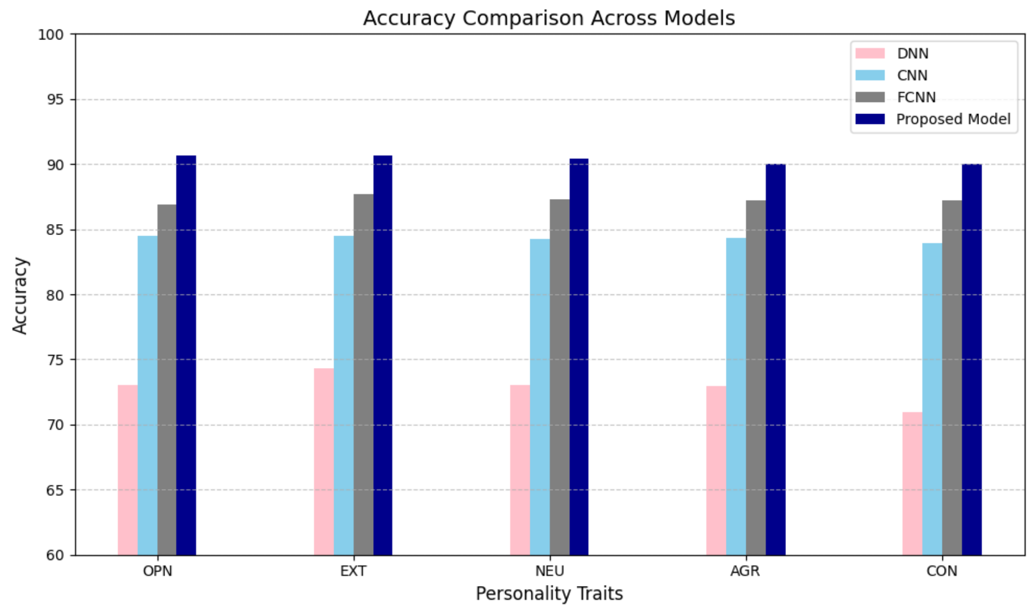

Figure 4. Accuracy Comparisons

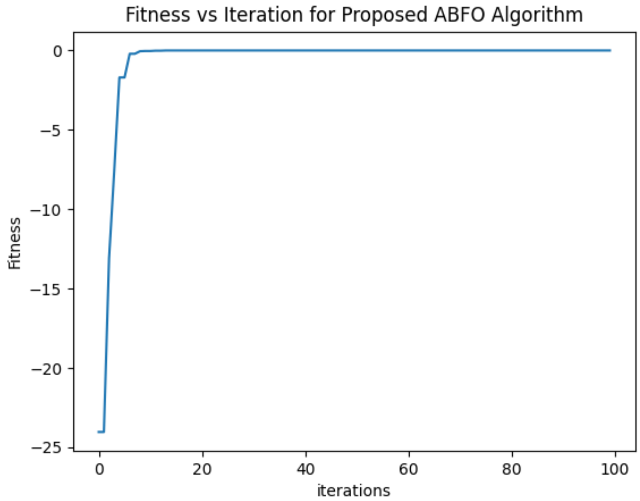

Figure 5. Optimization Fitness Graph

Overall the Proposed model shows a substantial improvement over the other models, indicating that this model is better suited for personality traits predictions based on the data. Performance comparison results from Proposed model with CNN and FCNN showed that the proposed approach is capable of capturing some improvements (e.g. feature selection, architecture design or hyper-parameter tuning) leading to an increase in accuracy and stability of predictions. The DNN has the lowest score, possibly because of the architecture limits or other issues that may prevent DNN from understanding the data correctly. In addition, each trait characterization result is independently obtained alongside each classifier using the predicted probability of 0 to 1 for the traits to carry out the classifier combination following the appropriate guidelines technique, as shown in Figure 4 the proposed model's highest accuracy. Based on the results of this study, personality traits, our proposed method performed better than other DL models, like FCNN, CNN and DNN individually, with the Proposed approach. The reason for optimization is to work on the performance and interpretability of a prescient model shown in Figure 5. The reason behind this outcome is the high dimensionality of elements on the dataset and extreme imbalanced classes. The most extreme fitness of this trait's characterization is 0 points with ABFO strategy. The recency-based memory forestalls patterns of length not exactly or equivalent to a predetermined number of emphases from occurring in the direction. It checks that the incorporation of fitness distance balance methodology and tumultuous neighborhood search into the algorithm can further develop the investigation capacity and investigate improved arrangements.

CONCLUSION

The model based on Big-Five personality, is used by the vast majority of personality-aware recommendation frameworks to address the client's personality. When compared to conventional recommendation strategies, personality-aware frameworks have an advantage, particularly when dealing with cold starting and information sparsity issues by FCNN with ABFO model with tent guide capability and the greatest accuracy, sensitivity, and specificity advantages of Personality Traits order like OPN, EXT, NEU, CON, and AGR. For each of the five traits, the proposed model achieves accuracy improvements over the best-in-class normal accuracy results. Our findings indicate that the provinces of DNN, CNN, and FCNN fine-tuned adequate information from a variety of big five personality information sources. The after-effect of the proposed model performed better contrasted with the non-streamlining classifier in the suggested informational collection with above 90% accuracy in ordinary. Utilizing goal tests, projections, and individual interviews in conjunction with a sufficient man-made consciousness algorithm can take results to the next level and yield a more precise result. In the future, we intend to work on the performance of continuous data sets using a comparable methodology, which could also be used to develop an algorithm that asses associations' personalities. To arrive at a flexible model that is utilized in the social organization domain, we also included additional concepts and subjectivity terms like opinions, feeling, feeling, and state of mind.

REFRENCES

[1] Rojas Q, Mario, David Masip, Alexander Todorov, and Jordi Vitria. "Automatic prediction of facial trait judgments: Appearance vs. structural models." PloS one 6, no. 8 (2011): e23323.

[2] Celli, Fabio. "Unsupervised personality recognition for social network sites." In Proc. of sixth international conference on digital society, pp. 59-62, 2012.

[3] Valente, Fabio, Samuel Kim, and Petr Motlicek. "Annotation and recognition of personality traits in spoken conversations from the ami meetings corpus." In Thirteenth annual conference of the international speech communication association, 2012.

[4] Zhang, Chen-Lin, Hao Zhang, Xiu-Shen Wei, and Jianxin Wu. "Deep bimodal regression for apparent personality analysis." In European conference on computer vision, pp. 311-324. Springer, Cham, 2016.

[5] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778, 2016.

[6] Xie, Saining, Alexander Kirillov, Ross Girshick, and Kaiming He. "Exploring randomly wired neural networks for image recognition." In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 1284-1293, 2019.

[7] Memon, Nimrabanu, Samir B. Patel, and Dhruvesh P. Patel. "Comparative analysis of artificial neural network and XGBoost algorithm for PolSAR image classification." In International Conference on Pattern Recognition and Machine Intelligence, pp. 452-460. Springer, Cham, 2019.

[8] Fatimah, Sri Hastuti, Esmeralda C. Djamal, Ridwan Ilyas, and Faiza Renaldi. "Personality features identification from handwriting using convolutional neural networks." In 2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), pp. 119-124. IEEE, 2019.

[9] Wu, Fan, Juelin Zhu, and Xiaomeng Guo. "Fingerprint pattern identification and classification approach based on convolutional neural networks." Neural Computing and Applications 32, no. 10 , pp. 5725-5734, 2020.

[10] Suen, Hung-Yue, Kuo-En Hung, and Chien-Liang Lin. "TensorFlow-based automatic personality recognition used in asynchronous video interviews." IEEE Access 7 , pp. 61018-61023, 2019.

[11] Zhu, Hancheng, Leida Li, Hongyan Jiang, and Allen Tan. "Inferring personality traits from attentive regions of user liked images via weakly supervised dual convolutional network." Neural Processing Letters 51, no. 3 , pp. 2105-2121, 2020.

[12] Chen, Chaofan, Oscar Li, Daniel Tao, Alina Barnett, Cynthia Rudin, and Jonathan K. Su. "This looks like that: DL for interpretable image recognition." Advances in neural information processing systems 32 , 2019.

[13] Yu, Jianguo, Konstantin Markov, and Alexey Karpov. "Speaking style based apparent personality recognition." In International Conference on Speech and Computer, pp. 540-548. Springer, Cham, 2019.

[14] Shuster, Kurt, Samuel Humeau, Hexiang Hu, Antoine Bordes, and Jason Weston. "Engaging image captioning via personality." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 12516-12526, 2019.

[15] Vijayakumar, Sowmya, Ronan Flynn, and Niall Murray. "A comparative study of machine learning techniques for emotion recognition from peripheral physiological signals." In 2020 31st Irish Signals and Systems Conference (ISSC), pp. 1-6. IEEE, 2020.

[16] Adi, Gabriel Yakub NN, Michael Harley Tandio, Veronica Ong, and Derwin Suhartono. "Optimization for automatic personality recognition on Twitter in Bahasa Indonesia." Procedia Computer Science 135 (2018): 473-480.

[17] Ahmad, Hussain, Muhammad Usama Asghar, Muhammad Zubair Asghar, Aurangzeb Khan, and Amir H. Mosavi. "A hybrid DL technique for personality trait classification from text." IEEE Access 9 (2021): 146214-146232.

[18] El-Demerdash, Kamal, Reda A. El-Khoribi, Mahmoud A. Ismail Shoman, and Sherif Abdou. "DL based fusion strategies for personality prediction." Egyptian Informatics Journal (2021).

[19] Quwaider, Muhannad, Abdullah Alabed, and Rehab Duwairi. "The impact of video games on the players behaviors: A survey." Procedia Computer Science 151 (2019): 575-582.

[20] Biswas, K., Shivakumara, P., Pal, U., Chakraborti, T., Lu, T. and Ayub, M.N.B., 2022. Fuzzy and genetic algorithm based approach for classification of personality traits oriented social media images. Knowledge-Based Systems, 241, p.108024.

[21] Rani, M. Jansi, M. Karuppasamy, and M. Prabha. "Bacterial foraging optimization algorithm based feature selection for microarray data classification." Materials Today: Proceedings (2021).

[22] Souri, Alireza, Shafigheh Hosseinpour, and Amir Masoud Rahmani. "Personality classification based on profiles of social networks' users and the five-factor model of personality." Human-centric Computing and Information Sciences 8, no. 1 (2018): 1-15.

[23] Sanyal, Oindrila, and Subhankar Das. "Big Five Personality Trait Analysis From Random EEG Signal Using Convolutional Neural Network." International Journal of Advanced Research in Computer Science 11, no. 2 , 2020.

[24] Mafla, Andres, Sounak Dey, Ali Furkan Biten, Lluis Gomez, and Dimosthenis Karatzas. "Fine-grained image classification and retrieval by combining visual and locally pooled textual features." In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 2950-2959, 2020.

[25] Dotti, Dario, Esam Ghaleb, and Stylianos Asteriadis. "Temporal triplet mining for personality recognition." In 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), pp. 379-386. IEEE, 2020.

[26] Moreno-Armendáriz, Marco A., Carlos Alberto Duchanoy Martínez, Hiram Calvo, and Miguelangel Moreno-Sotelo. "Estimation of personality traits from portrait pictures using the five-factor model." IEEE Access 8 , 201649-201665, 2020.

[27] Audet, Élodie C., Shelby L. Levine, Ezelbahar Metin, Sophie Koestner, and Stephanie Barcan. "Zooming their way through university: Which Big 5 traits facilitated students' adjustment to online courses during the COVID-19 pandemic." Personality and Individual Differences 180 (2021): 110969.

[28] Xu, Jia, Weijian Tian, Guoyun Lv, Shiya Liu, and Yangyu Fan. "Prediction of the Big Five Personality Traits Using Static Facial Images of College Students With Different Academic Backgrounds." IEEE Access 9 (2021): 76822-76832.

[29] Alsuliman, Maraheb, and Heyam H. Al-Baity. "Efficient diagnosis of autism with optimized machine learning models: An experimental analysis on genetic and personal characteristic datasets." Applied Sciences 12.8 (2022): 3812.

[30] Zaman, Khalid, et al. "Driver emotions recognition based on improved faster R-CNN and neural architectural search network." Symmetry 14.4 (2022): 687.

[31] Salahat, Mohammed, et al. "Personality Assessment Based on Natural Stream of Thoughts Empowered with Machine Learning." Computers, Materials & Continua 76.1 (2023).

[32] Lin, Hao, Chundong Wang, and Qingbo Hao. "A novel personality detection method based on high-dimensional psycholinguistic features and improved distributed Gray Wolf Optimizer for feature selection." Information Processing & Management 60.2 (2023): 103217.

[33] Khosravi, Sara. "Chimp optimization algorithm to optimize a convolution neural network for skin detection in HVS and RGB images." International Journal of Nonlinear Analysis and Applications 15.4 (2024): 275-284.

[34] Arfaoui, Nouha, et al. "Unveiling Human Essence: Deep Learning in Personality Traits Detection." International Journal of Computer Information Systems and Industrial Management Applications 17 (2025): 20-20.

[35] Madan, Surbhi, et al. "Explainable human-centered traits from head motion and facial expression dynamics." PloS one 20.1 (2025): e0313883.