International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 4 Volume No.8 July - August – 2024
DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

Automatic Personality Recognition

Naheed Sultana, Assistant Professor
B. Nikhitha[#1], N. Preethi[*2], P. Vaishnavi[#3]
Department of Information Technology, Stanley College of Engineering and Technology for Women, Hyderabad

***Abstract*—** Personality refers to the distinct characteristics and patterns of behaviour that define how an individual responds to various situations. Recognizing personality is crucial in various contexts, such as job interviews, mental health care, and investigations. In the realm of recruitment, understanding a candidate's personality can help organizations determine if the individual is well-suited for a specific role. This is particularly important in public sector jobs, where personality assessments often play a significant role in the selection process. Traditionally, personality recognition is conducted through psychometric tests, where individuals respond to a series of questions, and their personalities are inferred from their answers. However, this method may not always yield accurate results. To address this, this paper aims to predict personality traits by analysing video footage of individuals using advanced technologies such as OpenCV, Convolutional Neural Networks (CNNs), image detection, and the VGG-16 architecture. For this paper, we utilize the AffectNet dataset, which includes approximately 15,000 images representing three specific personality traits: confidence, nervousness, and confusion. By detecting facial features in the video and applying our model, we can predict these personality traits.
***Keywords*— Convolution Neural Networks, OpenCV, VGG-16 Architecture.**

I. INTRODUCTION

Automatic personality recognition is an intriguing interdisciplinary field that merges psychology, artificial intelligence, and computer vision. The objective of this paper is to develop a system based on Convolutional Neural Networks (CNNs) to automatically recognize personality traits from facial images. Personality, a multifaceted psychological construct, traditionally requires assessment through self-report questionnaires or observer ratings, which can be subjective and time-consuming. This paper aims to harness advancements in deep learning and computer vision to create a more efficient and objective method for personality assessment. Convolutional Neural Networks have demonstrated exceptional performance in various image-related tasks, including object recognition, image classification, and facial analysis. By training a CNN on a dataset of facial images annotated with personality traits, the network can learn to automatically extract relevant features and patterns associated with different personality traits. The proposed CNN architecture will include multiple convolutional layers to capture and extract features from the images, followed by pooling layers to reduce dimensionality and retain important information. These layers will be succeeded by fully connected layers that will classify the extracted features into specific personality traits. During the training phase, the network will learn to map facial features to corresponding personality traits using backpropagation and gradient descent optimization techniques. By automating personality recognition with a CNN-based system, this paper aims to provide a more objective, efficient, and scalable approach to personality assessment, potentially revolutionizing applications in recruitment, mental health, and various other fields. The importance of personality analysis in various fields, such as psychology, human- computer interaction, and job recruitment. The discuss previous work in the field of personality recognition, highlighting the use of various machine learning techniques, such as support vector machines, decision trees, and random forests, and the use of different types of features, including speech, text, and facial expressions. The Convolutional neural network (CNN) to analyse nonverbal cues and ascribe personality attributes based on facial expressions and self-reported questionnaires. Results of their experiment, which shows that their AI-based interview agents can correctly detect an interviewee's big-five qualities with an accuracy ranging from 81% to 87.5%. The semi super- vised DL technique performed well despite the lack of large-scale data and labour -Intensive manual annotation and labelling[1]. Faking is a phenomenon where individuals intentionally alter their responses on self-report questionnaires.

This behaviour is fairly common, with many studies showing that a notable portion of people engage in faking to some degree There are different types of faking behaviour, primarily impression management and self-deceptive enhancement. Impression management involves consciously manipulating responses to create a favourable impression. These different faking behaviours are associated with distinct individual differences. For instance, people with high levels of certain personality traits, like conscientiousness or neuroticism, may be more prone to impression management, while those with higher self-esteem might engage more in self- deceptive enhancement. The consequences of faking can be significant. In terms of measurement validity, faking can compromise the accuracy of self-report tools, leading to skewed data that do not accurately reflect the respondents' true characteristics or behaviours. Faking can also impact subsequent outcomes like job performance, as decisions based on inaccurate data may lead to poor job fit and lower performance levels. Overall, understanding and addressing faking behaviour is important for improving the reliability and validity of self-report measures and ensuring better outcomes in various contexts, such as employment and psychological assessment[2]. The work titled "Multimodal Analysis of Personality Traits on Videos of Self-Presentation and Induced Behaviour" introduces an innovative method for analysing personality traits through audio-visual inputs and transcribed speech. The researchers have designed deep learning models to estimate the Big Five personality traits by examining various behavioural cues, such as facial expressions, gestures, and voice. This study builds on prior research in personality analysis, emphasizing the significance of multimodal behavioural cues in assessing personality. A new dataset, the Self-Presentation and Induced Behaviour Archive for Personality Analysis (SIAP), is introduced. This dataset includes recordings of both induced behaviour and self- presentation, setting it apart from existing datasets in the field[3]. Study aimed at predicting perceived personality traits from audiovisual data, focusing on the Big Five personality traits model. This includes neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. A multimodal approach for predicting these traits from short video clips by utilizing audio features, global motion energy features, and facial landmark features is employed. To achieve this random decision forest regression model to make predictions based on the extracted features is used. Specifically, random decision forest with 5000 trees is used to perform regression on a 62-dimensional feature vector for each video, training a separate random decision forest for each of the personality traits. During the training phase, videos are excluded with problematic lighting conditions, camera angles, and pose variations, as these represented only a small fraction (approximately 0.4%) of the training data. In the test phase, instances of missing features were also minimal (about 0.3%)[4]. The question of whether nonverbal cues can be effectively used to make meaningful personality attributions in employment interviews has been extensively researched. Numerous studies have investigated the influence of nonverbal behaviour on determining personality traits and its potential for predicting job performance. For instance, a study by Ambady and Rosenthal demonstrated that nonverbal cues, such as facial expressions and body language, could be accurately used to predict personality traits in job candidates. Additionally, Riggio et al. revealed that nonverbal cues were more effective than verbal cues in predicting job performance. Interviewers who received training to focus on nonverbal cues made more accurate hiring decisions[5]. Asynchronous video interviews (AVIs) from the applicant's perspective as a modern tool for personnel selection. Initially, the traditional face-to-face interviews, discussing inherent biases and limitations. Then explore the advent of AVIs, which enable candidates to record their responses to predetermined questions at their convenience, both in terms of time and location. AVIs in personnel selection, highlighting benefits such as increased efficiency and reduced travel costs. The focus then shifts to the applicants' experiences with AVIs,

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 4 Volume No.8 July - August – 2024
DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

detailing the advantages and disadvantages from their viewpoint. The applicants perceptions of AVIs, noting potential issues like anxiety and stress from recording a video interview, along with concerns about privacy and data security[6].

II. METHODOLOGY

The architecture for facial emotion recognition integrates several key components to process and analyse facial expressions in real- time. It begins with a facial emotion dataset, which undergoes preprocessing to standardize the images through normalization, grayscale conversion. These images are then resized and features are extracted using techniques like convolutional neural networks (CNNs). The extracted features are used to train a model, which is tested for accuracy and saved for future use. The system captures real-time video input from a user's camera, which is fed into the saved model for immediate emotion prediction. Additionally, the live video feed can be saved for further analysis. This comprehensive process ensures efficient and accurate emotion detection, leveraging both static datasets and dynamic user inputs.

1. **Convolutional Layers:** VGG16 consists of 13 convolutional layers with small 3x3 filters applied with a stride of 1 and paddingto preserve the spatial resolution of the input.
2. **Pooling Layers:** Five max-pooling layers, each using 2x2 filters with a stride of 2, follow certain sets of convolutional layers to reduce the spatial dimensions progressively. Fully Connected Layers: The architecture includes three fully connected 21 layers at the end, where the first two have 4096 neurons each and use the ReLU activation function. The final fully connected layer serves as the output layer with softmax activation for classification tasks.

Activation Functions: ReLU (Rectified Linear Unit) activation is used for all convolutional and fully connected layers except the output layer. ReLU introduces non-linearity, which helps the network learn complex patterns, and also mitigates the vanishing gradient problem.

3. **Fully Connected Layers:** Fully connected layers use ReLU activation, except for the final output layer which typically uses softmax for classification tasks.
4. **Output Layer:** The output layer in a classification task uses the softmax activation function to produce probability distributions over classes. Here is a brief outline of the VGG16 architecture with the use of ReLU activations: Conv Layer (ReLU) -> Conv Layer (ReLU) -> Max Pooling Conv Layer (ReLU) -> Conv Layer (ReLU) -> Max Pooling Conv Layer (ReLU) -> Conv Layer (ReLU) -> Conv Layer (ReLU) -> Max Pooling Conv Layer (ReLU) -> Conv Layer (ReLU) -> Conv Layer (ReLU) -> Max Pooling Conv Layer (ReLU) -> Conv Layer (ReLU) -> Conv Layer (ReLU) -> Max Pooling 22 Fully Connected Layer (ReLU) -> Fully Connected Layer (ReLU) -> Fully Connected Layer (Softmax) By using ReLU activations throughout the network, VGG16 is able to effectively learn and represent complex patterns in the input data.

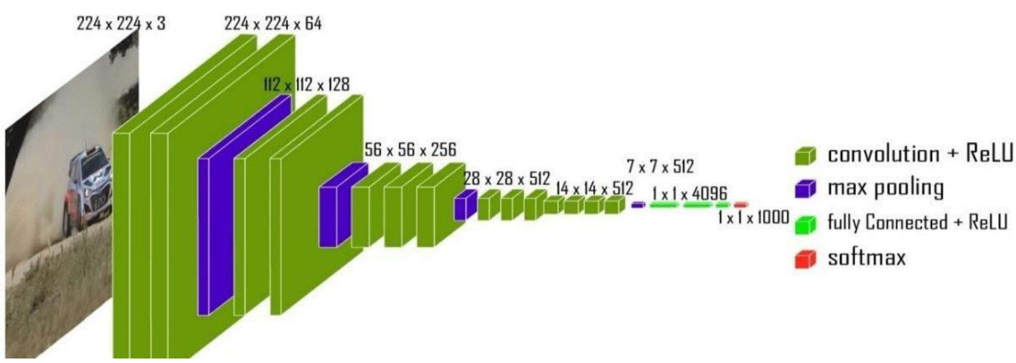

Fig 1: VGG 16 Architecture

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 4 Volume No.8 July - August – 2024
DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

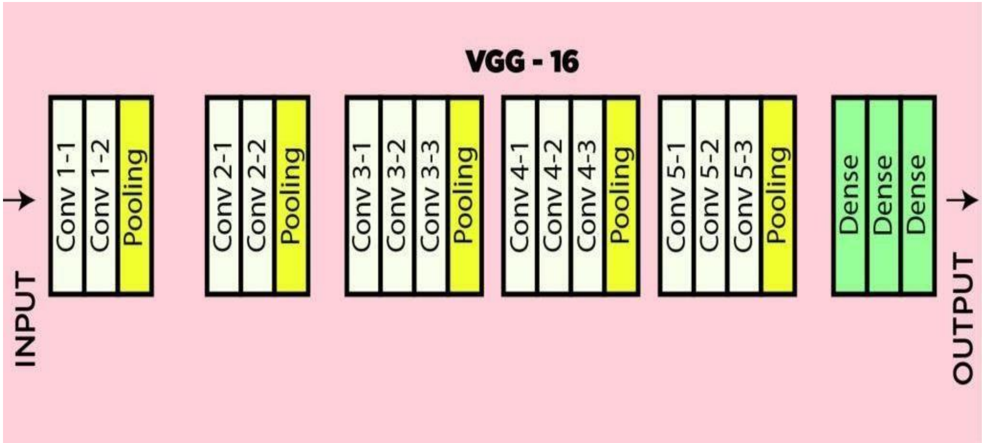

Fig 2: Convolution Layers

III. MODULES

Dataset: Accessing the Affectnet dataset from Kaggle is not a hassle. Registration on thewebsite with a valid mail id and acceptanceof their Terms of Use is necessary. Once registered, the dataset can be downloaded entirely or by specific subsets, the data is structured into folders for the three personality traits. The size of the dataset is nearly 300MB and the dataset consists of nearly 1500 images of each personality trait that hasbeen taken into consideration.

Data Preprocessing: Facial Detection is done using Opencv and MTCNN and the preprocessing is done internally using the tensor flow Library. Resizing the frames, eliminating undesiredobjects, conversion of image into gray scale ,correcting the texture and edges of the image come under data preprocessing.

Data Labelling: The dataset is labelled according to the personality trats that've been chosen. Thepersonality traits are confident, nervous and confused hence the traits are labelledaccordingly.

Model Architecture and Training: A suitable CNN architecture is chosen for feature Extraction and classification, the model that is being used is V66-16.There are other models like ResNet, DenseNet but VGG-16 is more effective. Hence VGG-16 is the selected model for feature extraction. Extracted Data is given to the model and training is done for prediction. Trainingof the model is important so that the model understands the emotions and traits of peopleand understand which emotion can be categorized under a trait, so that the detection of face will also be accurate and the personality trait predicted will be accurate.

Feature Extraction: The features that are considered to ne important for predicting personality are facial expressions, Eye contact, eye gestures, smile, foreseeing and etc. The dimensionality decrease process, what separates and lessens an underlying arrangement of crude information into additional sensible gatherings, include feature extraction. It will in this manner be easier to process when you need to. These enormousinformational collections' overflow of factors is by a long shot their most huge component. Handling these factors takes a ton of computer power. Accordingly, featureextraction productively lessens how much information by picking and joining factors into elements to assist with removing the best component from those huge informational indexes. These qualities are easy to deal with while precisely and innovatively portraying the genuine informational collection. They serve as a general description of the image's color statistics.

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 4 Volume No.8 July - August – 2024
DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

Confident: If a person is considered to be confident he has topossess these following features(Upright Posture, Direct eye contact, Controlled Gestures)
Nervousness: Fidgeting, Lack of eye contact, Excessive blinking, Sweating

Confusion: Furrowed Brows, Head tilting, Frequent looking around

IV. RESULTS

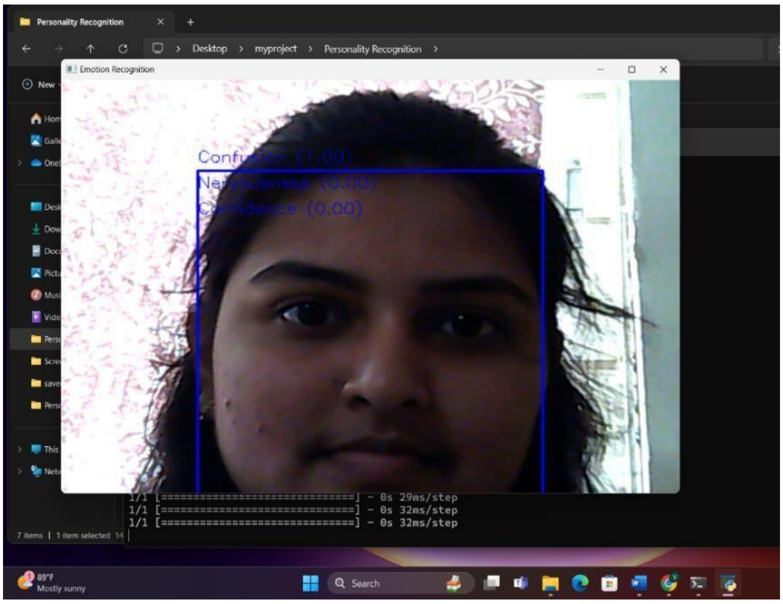

Fig 3: Predicted Traits

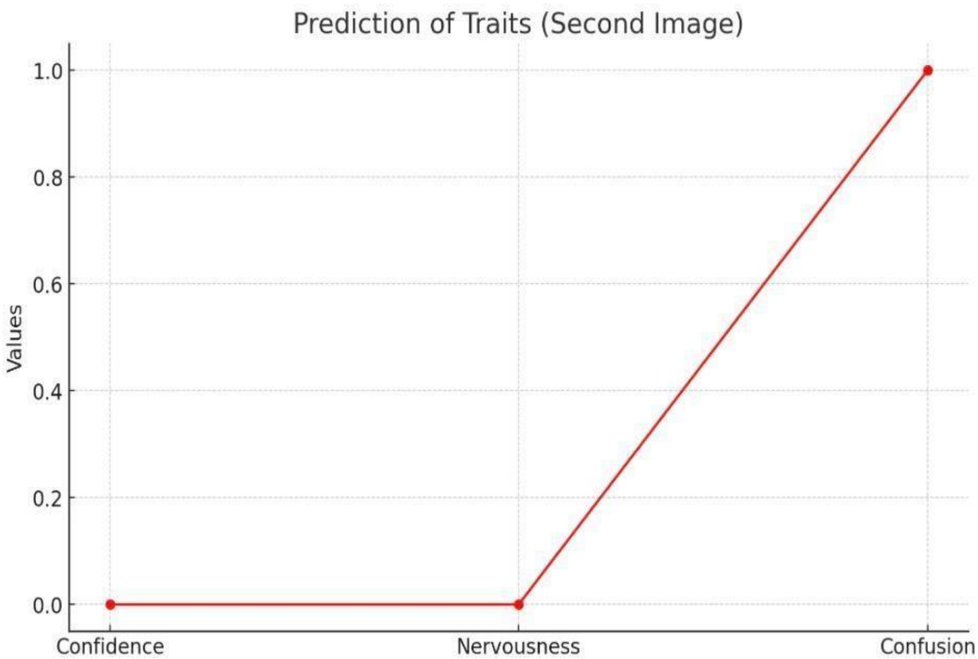

Fig 4: Graph for Predicted Traits

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 4 Volume No.8 July - August – 2024
DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

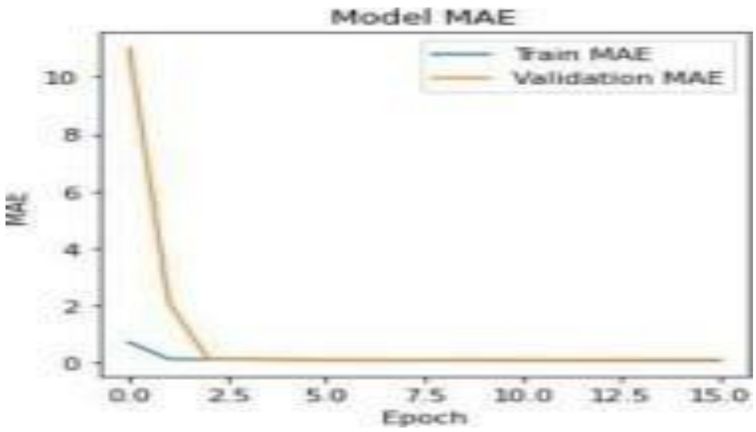

Fig 5: Loss (Mean Accuracy Error Vs Epoch)

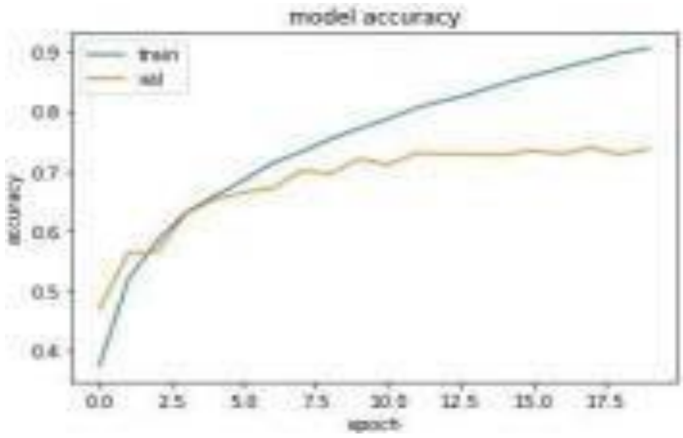

Fig 6: Accuracy (accuracy Vs epoch)

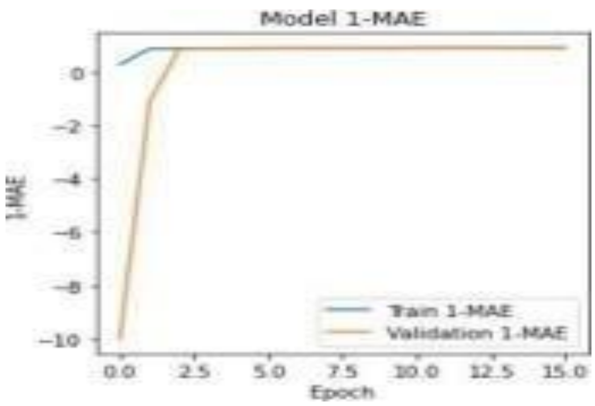

Fig7: evaluation metric 1-mae

DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

V. CONCLUSION

In conclusion, the paper outlined here presents an innovative approach to automatic personality recognition using Convolutional Neural Networks (CNNs). By leveraging advancements in deep learning and computer vision, this paper aims to overcome the limitations of traditional personality assessment methods, such as self- report questionnaires or observer ratings, which can be time-consuming and subjective.Through the proposed CNN-based system, the paper seeks to offer a more efficient and objective approach to personality assessment, utilizing facial images as input data.CNNs have demonstrated remarkable success in various image- related tasks, making them well-suited for extracting relevant features and patterns associated with different personality traits. The proposed CNN architecture will consist of multiple convolutional layers followed by pooling layers for feature extraction, followed by fully connected layers for classification. Through the training phase, the network will learn to map facial features to specific personality traits via back propagation and gradient descent optimization. Overall, this paper has the potential to contribute significantly to the interdisciplinary field of automatic personality recognition, offering a novel and data- driven approach that could enhance our understanding of personality traits and their manifestation in facial expressions.

ACKNOWLEDGMENT

Initially and foremost, We would like to sincerely thank Naheed Sultana, our project supervisor, for all of her support and encouragement during the project. Her knowledge and perceptive feedback have been really helpful for molding our work and assisting us in overcoming obstacles. We would like to express our sincere gratitude to Dr. Badugu Srinivasu our head of the department and the faculty members of IT department for their assistance and for giving the tools and resources that were needed to finish this project successfully. We also want to express our sincere gratitude to our friends for their unwavering support, encouragement, and for fostering a collaborative environment that has made this journey both joyful and enriching.

REFERENCES

[1] Hafsa Fatima and Abdul Bari Mohammed.“TENSORFLOW-BASED AUTOMATO PERSONALITY RECOGNITIONUSED IN ASYNCHRONOUS

[2] Chalearn.FirstImpressionsV2(CVPR’17).2023.url: https://chalearnlap.cvc.uab.cat/dataset/24/description/ (visitedon03/09/2023).Heysem Kaya, FurkanGu¨rpınar, andAlbert Salah. “Multi-modal Score FusionandDecision Trees for ExplainableAutomaticJobCandidate Screening fromVideo CVs”. In: July2017. doi: 10.1109/CVPRW.2017. 210.

[3] Dersu Giritlioglu, Burak Mandıra, Selim Yilmaz, Ufuk Ertenli, Berhan Akgu¨r, Aslı Gu¨l Kurt, EmreMutlu, Seref Can Gurel, and Hamdi Dibeklioglu. “Multimodal analysis of personality traits videos of self- presentation and induced behavior”.In: Journal on Multimodal User Interfaces 15(Nov.2020). doi: 10.1007/s12193-020-00347-7.

[4] Evgeny Osin, Denis Davydov, Konstantin Shatalov,and Alexey Novok- shonov. “AssessingtheBigFivepersonality traits using real-life staticfa-cialimages”. In: Scientific Reports 10 (May2020). doi:10.1038/s41598- 020-65358-6.

[5] Jelena Gorbova, Iiris Lusi, Andre Litvin, and Gholamreza Anbarjafari. “Automated Screening of JobCandidate Based on Multimodal Video Processing”. In: July 2017, pp. 1679–1685. doi: 10.1109/CVPRW.2017. 214.

[6] VIDEO INTERVIEWS”. In: ITBJournal ofEngineering Science Vol 13 (May 2022), p. 268.

[7] Matthew Mclarnon, Amanda DeLongchamp, andTravis Schneider. “Fak- ing it! Individualdifferencesin types and degrees of fakingbehavior”. In: Personality andIndividualDifferences 138 (Sept. 2018), pp. 88–95. doi:10.1016/j.paid.2018.09.024.

[8] Timothy DeGroot and Janaki Gooty. “CanNonverbal Cues be Used to Make Meaningful

DOI:10.46647/ijetms.2024.v08i04.019 ISSN: 2581-4621

Personality Attributions in Employment Interviews?” In: Journal of Business and Psychology 24 (June 2009), pp. 179–192. doi:10.1007/s10869-009-9098-0.
[9] Ann Ryan, Matt Reeder, Juliya Golubovich, JamesGrand, Inceoglu Ilke, Dave Bartram, EvaDerous,Ioannis Nikolaou, and Xiang Yao. “CultureandTesting Practices: Is the World Flat?” In: AppliedPsychology 66 (Mar. 2017). doi:10.1111/apps.12095.
[10] Ricardo Camati and Fabr´ıcio Enembreck. “Text- Based Automatic Per- sonality Recognition: a Projective Approach”.In: Oct. 2020, pp. 218–225. doi: 10.1109/SMC42975.2020.9282859.
[11] Alan Gow, Martha Whiteman, Alison Pattie, and Ian Deary. “Goldberg’s ‘IPIP’ Big-Five factor markers: Internal consistency and concurrent vali- dation in Scotland”. In: Personality and Individual Differences 39 (July 2005), pp. 317–329. doi: 10.1016/j.paid.2005.01.011.
[12] Dena F. Mujtaba and Nihar R. Mahapatra. “Multi- Task Deep Neural Networks for Multimodal Personality Trait Prediction”. In: 2021 Inter- national Conference on Computational Science and Computational Intelligence (CSCI). 2021, pp. 85– 91. doi: 10.1109/CSCI54926.2021.00089