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TENSORFLOW-BASED AUTOMATIC PERSONALITY RECOGNITION USED IN ASYNCHRONOUS VIDEO INTERVIEWS

1.Hafsa Fatima , fatimahafsa302@gmail.com
2.Shayesta Nazneen ,shtnazn@gmail.com
3.Maryam Banu, mohammadtalib90636@gmail.com

Under guidance of Dr. Mohammed Abdul Bari, drabdulbari@isl.edu.in

ABSTRACT: With the development of artificial intelligence (AI), the automatic analysis of video interviews to recognize individual personality traits has become an active area of research and has applications in personality computing, human-computer interaction, and psychological assessment. Advances in computer vision and pattern recognition based on deep learning (DL) techniques have led to the establishment of convolutional neural network (CNN) models that can successfully recognize human nonverbal cues and attribute their personality traits with the use of a camera. In this study, an end-to-end AI interviewing system was developed using asynchronous video interview (AVI) processing and a TensorFlow AI engine to perform automatic personality recognition (APR) based on the features extracted from the AVIs and the true personality scores from the facial expressions and self-reported questionnaires of 120 real job applicants. The experimental results show that our AI-based interview agent can successfully recognize the "big five" traits of an interviewee at an accuracy between 90.9% and 97.4%. Our experiment also indicates that although the machine learning was conducted without large-scale data, the semisupervised DL approach performed surprisingly well with regard to automatic personality recognition despite the lack of labor-intensive manual annotation and labeling. The AI-based interview agent can supplement or replace existing self-reported personality assessment methods that job applicants may distort to achieve socially desirable effects.

Keywords- *Deep learning, Convolutional neural network, Asynchronous video interview, Automatic personality recognition.*

1. INTRODUCTION

Industrial and organizational (I/O) psychologists have found that personality is a global predictor used in employment selection [1]. Some employers use selfreported surveys to measure job applicants' personalities; however, job applicants may lie when self-reporting personality traits to gain more job opportunities [2]. Some employers evaluate the applicants' personalities from their facial expressions and other nonverbal cues during job interviews because applicants have considerable difficulty faking nonverbal cues [3]. However, it is not practical for every job applicant to attend a live job interview in person or participate in interviews conducted through telephone calls or web conferences due to the cost and time limitations [4]. One-way asynchronous video interview (AVI) software can be used to automatically interview job applicants at one point in time. This approach allows employers to review the audio-visual records at a later point in time [5]. When using AVI, human raters find it cognitively challenging to correctly assess applicants' personality traits based on video images [6]. Barrick et al. [7] found that human raters were unable to accurately assess an applicant's personality simply by watching recorded-video interviews.

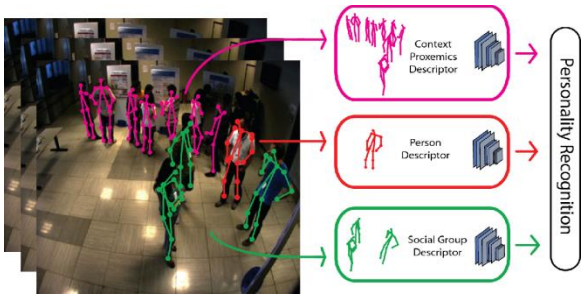

Fig.1: Example figure

Both I/O psychology and computer science scholars have suggested that artificial intelligence (AI) may surpass humans in recognizing or predicting an applicant's personality for screening job applicants because applying AI techniques to audio-visual datasets can achieve more reliable and predictive power than human raters [8]–[11]. "AI is a branch of computer science that seeks to produce intelligent machines that respond in a manner similar to human intelligence" [12], and it "aims to extend and augment human capacity and efficiency of mankind

in tasks of remaking nature" [13]. Machine learning (ML) is a major approach for achieving AI, which "gives computers the ability to learn without being explicitly programmed" [14]. Deep learning (DL) is a technique to implement ML, and it can "mimic the human brain mechanism to interpret data such as images, sounds and texts" [15]. In contrast to traditional ML, DL feature extraction is automated rather than manual [12]. ML/DL can be divided into supervised learning, unsupervised learning, and semi-supervised learning [12]. Supervised learning tasks are commonly conducted by classification using predefined labeled training data (called "ground truth"), whereas unsupervised learning can automatically learn the correct answers from a large amount of data without requiring predefined labels [10], [16]. Semisupervised learning combines those two approaches by using relatively smaller amounts of unlabeled data plus some labeled data for pattern recognition; therefore, this approach can reduce labeling efforts yet still achieve high accuracy.

2. LITERATURE REVIEW

2.1 Culture and testing practices: is the world flat?

Much has been speculated regarding the influence of cultural norms on the acceptance and use of personnel selection testing. This study examined the cross-level direct effects of four societal cultural variables (performance orientation, future orientation, uncertainty avoidance and tightness-looseness) on selection practices of organizations in 23 countries. 1,153 HR professionals responded to a survey regarding testing practices in hiring contexts. Overall, little evidence of a connection between cultural practices and selection practices emerged. Implications of these findings for personnel selection and cross-cultural research as well as directions for future work in this area are described**.**

2.2 Faking it! Individual differences in types and degrees of faking behavior:

Personality measures are commonly used in personnel selection and other high-stakes situations. In these settings , respondents may engage in purposeful deception, or faking, to increase the likelihood of receiving a valued outcome (i.e., being offered a job). However, some individuals may tend to only fake slightly, others may demonstrate more extreme response tendencies, and others may respond honestly. In this study, we used within-person, two-wave data to investigate faking on a conscientiousness measure across honest-responding and faking conditions using latent transition analysis (LTA) to identify different types of fakers. Agreeableness, neuroticism, and the perceived ability to deceive (PATD), obtained in the honest-responding condition, were used to predict faking behavior patterns. We also examined whether counterproductive workplace behavior (CWB) differed across the faking types. Results supported three-class solutions in both honest-responding and faking conditions, and that respondents could be classified as honest respondents, slight fakers, and extreme fakers. Results partially supported the role of high agreeableness and low neuroticism as predictive of stable response patterns. PATD results did not suggest a significant predictive relation with faking behavior. Extreme fakers were also found to generally exhibit the highest levels of CWBs. Implications and directions for continued research are discussed.

2.3 Can nonverbal cues be used to make meaningful personality attributions in employment interviews?

Purpose This study examines the role of personality attributions in understanding the relationships between nonverbal cues and interview performance ratings. Design/methodology/approach A structured behavioral interview was developed for identifying management potential in a large, national company. Using a concurrent design to validate the interview, managers were interviewed and the interviews were videotaped (n = 110). These videotapes were used as stimuli for raters in this study. Findings Results indicate that raters can make personality attributions using only one channel of information and these attributions partly explain the relationships between nonverbal cues and performance measures. Furthermore, conscientiousness attributions explain the relationship between visual cues and interview ratings, extraversion attributions mediate the relationship between vocal cues and interview ratings. Neuroticism attributions had a suppressing effect for both visual and vocal cues. Implications No matter how much an interview is structured, nonverbal cues cause interviewers to make attributions about candidates. If we face this fact, rather than consider information from cues as bias that should be ignored, interviewers can do a better job of focusing on job-related behavior and information in the interview, while realizing that the cues are providing information that must be attended to. Originality/value This study isolated the sources of information provided to raters to either the vocal or the visual channel to examine their impact individually. A Brunswik lens model shows the potential impact of personality attributions predicting

both job and interview performance ratings when both channels of information are used.

2.4 Asynchronous video interviewing as a new technology in personnel selection: the applicant's point of view:

The present study aimed to integrate findings from technology acceptance research with research on applicant reactions to new technology for the emerging selection procedure of asynchronous video interviewing. One hundred six volunteers experienced asynchronous video interviewing and filled out several questionnaires including one on the applicants' personalities. In line with previous technology acceptance research, the data revealed that perceived usefulness and perceived ease of use predicted attitudes toward asynchronous video interviewing. Furthermore, openness revealed to moderate the relation between perceived usefulness and attitudes toward this particular selection technology. No significant effects emerged for computer self-efficacy, job interview self-efficacy, extraversion, neuroticism, and conscientiousness. Theoretical and practical implications are discussed**.**

2.5 A survey of personality computing:

Personality is a psychological construct aimed at explaining the wide variety of human behaviors in terms of a few, stable and measurable individual characteristics. In this respect, any technology involving understanding, prediction and synthesis of human behavior is likely to benefit from Personality Computing approaches, i.e. from technologies capable of dealing with human personality. This paper is a survey of such technologies and it aims at providing not only a solid knowledge base about the state-of-the-art, but also a conceptual model underlying the three main problems addressed in the literature, namely Automatic Personality Recognition (inference of the true personality of an individual from behavioral evidence), Automatic Personality Perception (inference of personality others attribute to an individual based on her observable behavior) and Automatic Personality Synthesis (generation of artificial personalities via embodied agents). Furthermore, the article highlights the issues still open in the field and identifies potential application areas.

2.6 Improving socially-aware recommendation accuracy through personality:

In order to innovatively solve cold-start problems, research involving trust and socially aware recommender systems is currently proliferating. The relative importance of academic conferences has led to the necessity of recommender systems that seek to generate recommendations for conference attendees. In this paper, we aim to improve the recommendation accuracy of socially-aware recommender systems by proposing a linear hybrid recommender algorithm called Personality and Socially-Aware Recommender (PerSAR). PerSAR hybridizes the social and personality behaviours of smart conference attendees. Our recommendation methodology mainly aims to employ an algorithmic framework that computes the personality similarities and tie strengths of conference attendees so that effective and reliable recommendations can be generated for them using a relevant dataset. The experimental results substantiate that our proposed recommendation method is favorable and outperforms other related and contemporary recommendation methods and techniques.

3. IMPLEMENTATION

Previous automatic personality recognition (APR) studies were developed based on supervised ML, which involves manual labeling work and is time consuming. Because convolutional neural networks (CNNs) have been proven to be high-performing models that can automatically process images and infer first impressions from camera images, this study implemented semi-supervised DL methods, including CNNs, to develop an AI-based interview agent that can automatically recognize a job applicant's personality by using relatively smaller datasets of the applicants' facial expressions.

PERSONALITY TAXONOMY:

Personality refers to "individual differences in characteristic patterns of thinking, feeling, and behaving". This construct is commonly used to predict whether a job candidate will perform well in a specific job role and engage well in a prospective cultural environment. Although a variety of models can be used to assess personality, the "big five" traits, also called the five-factor model (FFM) or OCEAN model, provide researchers and practitioners with a well-defined taxonomy for selecting job applicants. The core factors of the big five are categorized and applied in different cultural contexts; these factors are openness, conscientiousness, extraversion, agreeableness, and neuroticism (low emotional stability).

- Openness: the degree to which an individual is imaginative and creative.

- Conscientiousness: the degree to which an individual is organized, thorough, and thoughtful.
- Extraversion: the extent to which an individual is talkative, energetic, and assertive.
- Agreeableness: the degree to which an individual is sympathetic, kind, and affectionate.
- Neuroticism: reflects the tension, moodiness, and anxiety an individual may feel.

Different approaches exist to measuring an individual's big five traits, including self-rating and observer-rating. Selfrating reflects self-image, whereas observer-rating reflects the subjective impressions perceived by others toward an individual's personality [7]. In the self-perspective approach, personality refers to a person's described motives, intensions, feelings, and past behaviors. From the observer's perspective, personality incorporates information about a person's social reputation, but valid observer-ratings should ideally be obtained by close acquaintances, such as partners, friends, or coworkers [19]. In the I/O psychology literature, when the valid observer-rated big five traits are difficult to assess, selfratings are the foundational information used to predict individual workplace behaviors and performance. Selfratings can also be used to predict whether a job candidate is a good fit for the job requirements and the organizational culture in a zero-acquaintance context, such as a job interview.

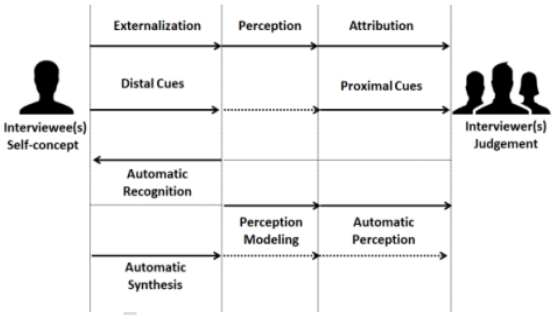

Fig.2: System architecture

PERSONALITY COMPUTING:

According to social information processing theory, people observe and interpret the cues exhibited by others and draw conclusions regarding their personalities during interactions such as interviews. Brunswik's lens model, depicted in Figure 2, illustrates how an interviewer uses cues to judge the interviewee's personality and to show the relationship between the interviewee's self-assessed personality and the interviewer's perceptual observations of personality regarding the interviewee [6].

By extracting features from the audio-visual data of AVI, APR is intended to auto-recognize an interviewee's selfassessed personality from distal cues. In contrast, APP is intended to auto-predict the observer-rated personality of an interviewee from proximal cues. Because examining proximal cues is not easy, APP instead uses distal cues as an approximation, as described. In APS, artificial agents, avatars, or robots are used to display human-like distal cues and the goal is for these cues to be perceived and inferred by humans as predefined traits. To develop AI-based APR, AVI can be adapted and combined with APR to auto-recognize interviewees' "true scores" compared to their self-rated personality traits.

4. ALGORITHM

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

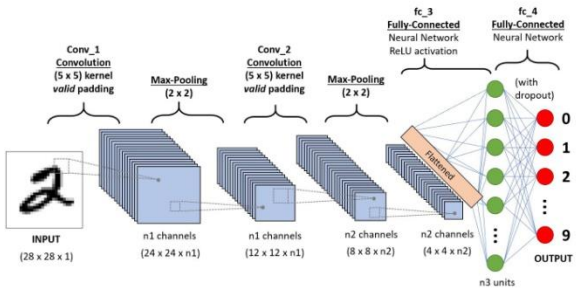

Fig.3: CNN model

CNN's were first developed and used around the 1980s. The most that a CNN could do at that time was recognize handwritten digits. It was mostly used in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a large amount of data to train and also requires a lot of computing resources. This was a major drawback for CNNs at that period and hence CNNs were only limited to the postal sectors and it failed to enter the world of machine learning.

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. When you input an image in a ConvNet, each layer generates several activation functions that are passed on to the next layer. The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges. As we move deeper into the network it can identify even more complex features such as objects, faces, etc.

5. EXPERIMENTAL RESULTS

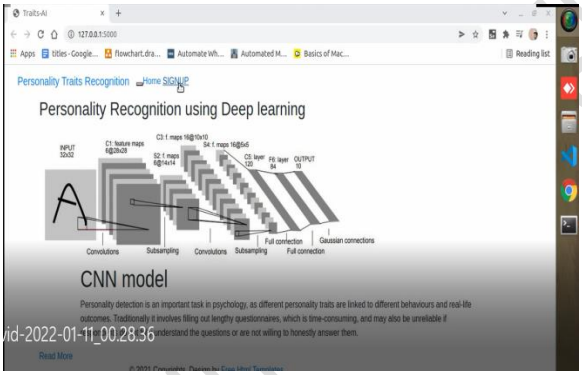

Fig.4: Home screen

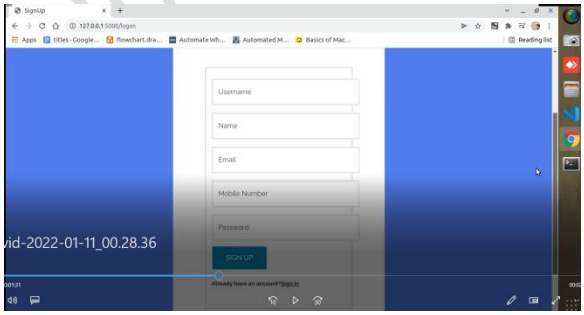

Fig.5: User registration

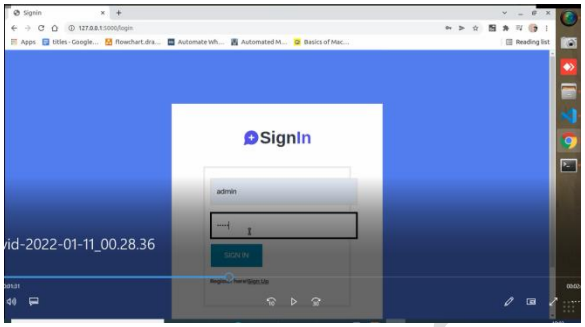

Fig.6: User login

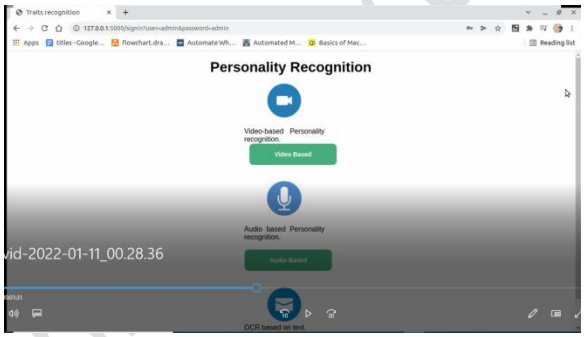

Fig.7: Main screen

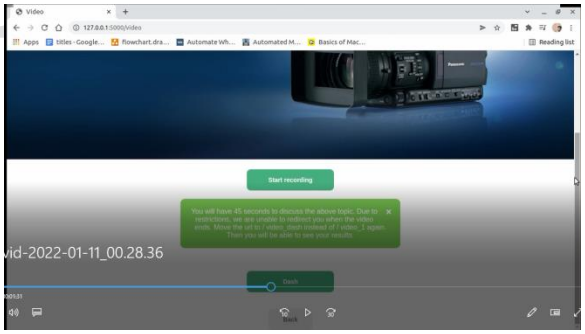

Fig.8: Video based recognition

Fig.9: Capture faces

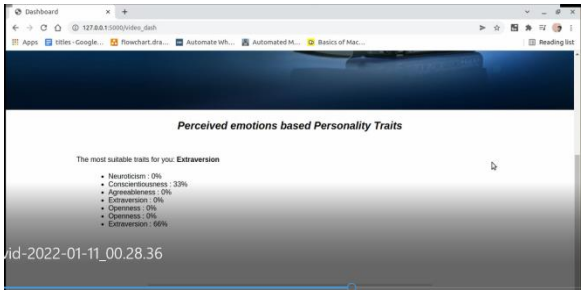

Fig.10: Result for video recognition

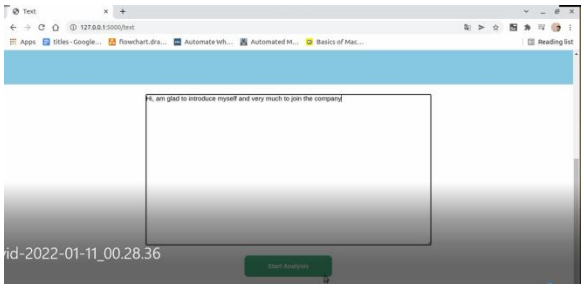

Fig.11:Text based recognition

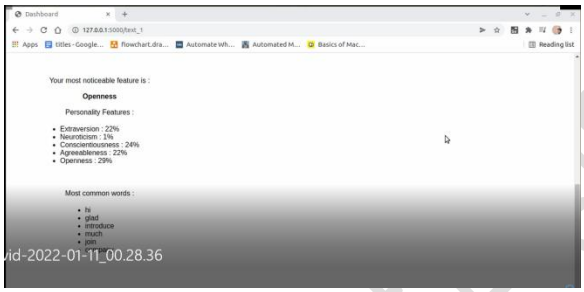

Fig.12: Result for text

6. CONCLUSION

This study is a response to the call for research into personality computing. In traditional personality computing, validating APR using manually labeled features from any possible detectable distal cues was quite complicated [6]. Thus, some recent studies have adopted DL-based architectures to predict personality based on third-party datasets, such as Amazon's Mechanical Turk or ChaLearn's First Impressions dataset. However, most of these studies used APP, in which the DL engines mimicked human raters as observers detecting an interviewee's nonverbal cues and made inferences concerning the interviewees' personality traits in the context of zero-acquaintance judgements. In other words, these experiments used subjective personality impressions rather than true personality scores [6] as the independent variables, which may have introduced existing bias. This paper developed an AVI embedded with a TensorFlow-based semi-supervised DL model to accurately auto-recognize an interviewee's true personality based on only 120 real samples of job applicants. Our APR approach achieved an accuracy above 90%, outperforming previous related laboratory studies whose accuracy ranged between 61% and 75% in the context of nonverbal communication [6]. The high-performing APR used in this AVI can be adopted to supplement or replace self-reported personality assessment methods that can be distorted by job applicants due to the effects of social desire to be selected for employment.

7. FUTURE SCOPE

Previous related studies have found that multimodal features (image frames and audio) learned by deep neural networks can deliver better performances in predicting the big five traits than can unimodal features. In future work, we may combine our visual approach with prosodic features to learn how to recognize an interviewee's personality. Moreover, this study utilized a specific type of professional as participants, which may limit the generalizability of these experimental results. Future research should include a more diverse participant population.

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