Emotion and Personality Analysis in Recorded Video Interview Using TensorFlow

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Abstract – Post Covid times have made it difficult to meet personally and get to know the potential candidates on individual basis. Although, advances in AI has made it possible to successfully recognize personality traits and other non-verbal cues with the help of camera. In this study, Convolutional neural network (CNN) using Deep learning (DL) has been taken in use to extract personality traits from video and speech feeds to output desired results.

Key Words: Convolutional Neural Network, Deep Learning, Artificial Intelligence, TensorFlow, Personality Computing

1. INTRODUCTION

It has been found that the personality is the preferred method of choosing an employee. Many job candidates can lie when they report their personality to get more career possibilities. Most organizations check candidates' personalities from their facial cues and other insignificant clues during job interviews because candidates have a serious problem making illegal references. However, it is not possible for everyone who applies for a job to attend a live interview or participate in telephone interviews due to limited time. Recorded video software can help to evaluate candidates simultaneously. This method lets the organization to check the recordings at any point of time. When assessing through the recorded interviews, HR's often find it a challenge to understand how to properly assess the personality traits of candidates depending on video images.

1.1 PERSONALITY TAXONOMY

Personality refers to “individual variation of patterns of thought, emotion and behaviour”. This structure is often used to predict that the candidate will perform well in a particular field of work and participate well in the future cultural environment. While a variety of models can be used to assess personality, the "five main features", also called the OCEAN model, provide researchers with a properly laid out classification of choice for candidates. The core elements of the five major divisions are subdivided and used in a variety of cultural contexts, and they are: neuroticism, extraversion, openness, agreeableness and conscientiousness.

1.2 PERSONALITY COMPUTING

In the context of the analysis of social data, people look at and elucidate the indications shown by others and reach conclusions about their personality during interactions such as interviews. Brunswik's lens model, shown in Figure1 shows that the interviewee uses certain methods to assess the interviewer's personality and perception of the interviewer.

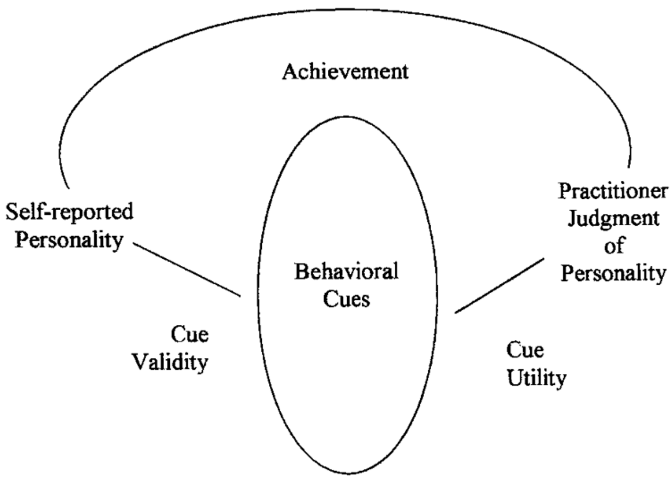

Fig-1. Brunswik's lens

Distal indicators (any visual indications that the HR can point out, such as visual expressions, look, body movements, and speech). Alternatively, Organizations often use “lens model” to identify the missing personality features of the interviewer by using descriptive definitions (i.e., any interviewed behavior observed by the HR; however, these references may translate to ideas from the organization.

Researchers, in their trials, have found that in addition to the face and muscle of applicants identified in asynchronously recorded interviews, the interviewer or character can still use non-verbal methods to judge the personality traits of the candidates. Few experimental studies have shown that a person can say that the acceptable personality traits of zero skeptics are based on short video. The personality computing, a new-age research field related to AI and human psychology, is used to automatically recognize and integrate personality and human behavior based on lens model. The 3 ways to use a computer to automatically detect personality is APR, automated personality synthesis (APS) and automatic personality perception (APP).

2. DATA PROCESSING

2.1 DATA COLLECTION

To organize the database in the actual context of a job interview, we created AVI-based software. We have used Google's cloud storage to access recorded information, create chat scripts, transfer video cues from interviews, and receive visual responses. The video responses can be used to perform algorithmic study, including AV analysis of the video responses. We conducted a study with help from a NGO organization Rotaract Club located in Thane, Maharashtra. We hosted a webpage giving access to their HR managers for hiring 2–3 Accounts candidate.

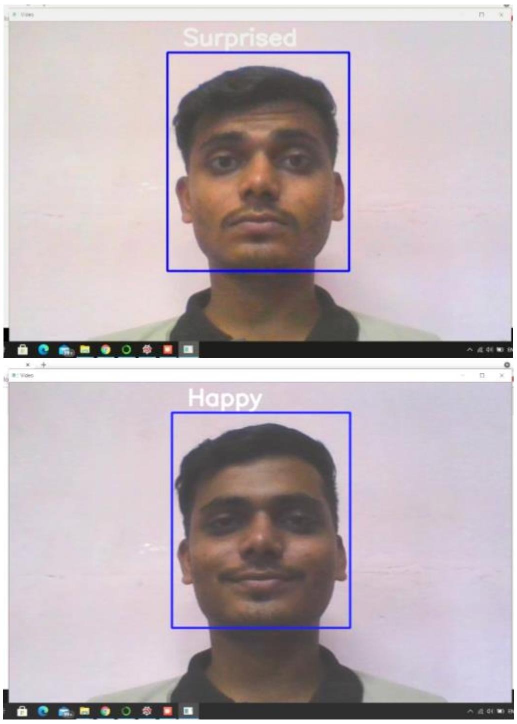

Fig-2. Face labeling

Resumes of candidates are uploaded and screened for desired job description, during this same process, other important information is also filtered out from resume like name, address, phone number, experience, skills, college name and previous organizations that the candidates have worked in. A total of 20 candidate's interview were held using this software. Once the resume is uploaded and screened for desired job description, the employer/HR starts the video emotion and speech emotion program to analyze the facial and tonal behavior. The interviewer asks one question at a time and waits for the candidate to reply. Once the candidate has given his response, the software analyses and tags the face and tone according to how the candidate has replied. The tone can range from under confident and angry to happy and confident. After this process, the employer/interviewer can access all this data in the organization website at later point of time to evaluate any specific candidate.

2.2 DATA LABELING

All candidates were given an online survey based on International Personality Item Pool (IPIP). Candidates were required to complete this survey before participating in the study. They were ensured that the survey results were only to be used for research purposes and not for actual employment recommendations. This ensures that the candidates appear for the interview without any social aspirations, as it can lead to unbalanced inputs in the software, which may hamper true readings and outputs.

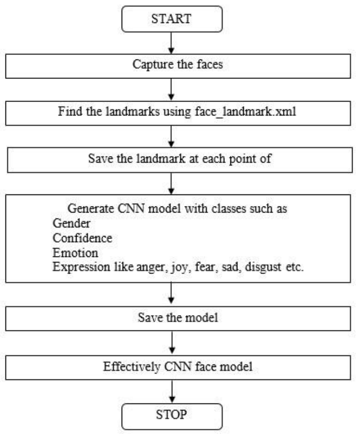

Fig-3. Face analysis

3. MODEL BUILDING

We have combined the personalized details of the 20 candidates and their features released to train the APR model, which used specific CNN built using the Python engine and TensorFlow deep learning. Before uploading images to the neural network model, we made things standard by adjusting the feature value range to [0, 1].
The extracted elements were then combined with other elements and presented in the extraction layer for final classification. Our CNN structure consists of four convolutional layers, three layers of integration, ten mixed layers, a fully integrated layer and a layer of softmax as a result.

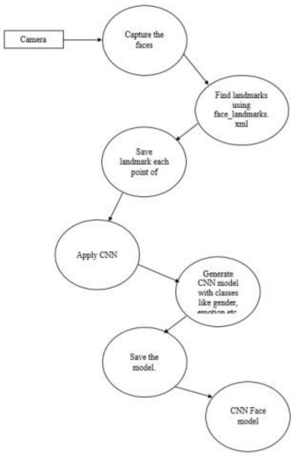

Fig-4. CNN Model

3.1 CRITERIA FOR THE ASSESSMENT

We used complementary variance to evaluate the effectiveness of APR so that we could measure how relative the new evaluation process (APR) was in line with the re-established evaluation process (reported inventory). We used the Pearson correlation coefficient (r) to measure the complementary validity in this experiment. In addition, we followed O. Celiktutan's paper for measuring determination coefficient (R^2) and the mean square error (MSE). The R^2 indicates the variance in the dependent variable (y) that can be predicted or defined by the predictor. The greater the R^2, the better the model is. The MSE measures the relative equality of the regression model; the larger this number is, the larger the error is.

4. RESULTS

In this study, the reliability of the construct was satisfactory because the validity analysis showed that the loading of each item was higher than 0.6, and the value of Kaiser-Meyer-Olkin (KMO) was more than 0.8. The reliability of internal consistency was good because Cronbach's alpha (α) values were greater than 0.7 as follows: Experience openness (α = .75), conscience (α = .83), extraversion (α = .88), agreeableness (α = .80), and neuroticism (α = .84).

All sizes of the five major features were read and successfully predicted by AI TensorFlow engine. All five major self-assessment statistics can be predicted by APR. Pearson correlation in the average size was between 0.966 and 0.976. R2 for each measure was between 0.933 and 0.953. All correlations were found to be significant (p <0: 01), while the MSE for each measure was between 0.053 and 0.120. If R2 rises (100% is ideal), it leads to better performance of estimator. On the other hand, the MSE decrease (0 is ideal), where estimator error is small.

5. CONCLUSION

Our APR method has achieved more than 85% accuracy, successfully performing previous laboratory studies related to their accuracy which was limited to 75% in the case of nonlinguistic communication. The effective APR used in this AVI can be accepted to append or replace personal self-assessment methods that may be impeded by job candidates as a result of the social aspirations for employment. Previous related studies have found that a variety of factors (picture and sound frames) studied by deep neural networks can bring better performance in predicting five major factors than unimodal factors. In the future scope, we can combine our visual approach with prosodic features to learn how to identify the individual personality of the person you are talking to. In addition, this study used a specific type of executives as participants, which could reduce the likelihood of these test results. Future research should include the number of diversified participants.

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