

Automatic Personality Recognition used in Asynchronous Videos

Nithya D M¹, Rakshith N J², Rohan K U³, Sneha C R⁴, Prof. Vimala Devi. R⁵

Final Year Student, Department of Information Science and Engineering^{1,2,3,4}

Assistant Professor, Department of Information Science and Engineering⁵

S J C Institute of Technology, Chikkaballapur, India

Abstract: *With the use of artificial intelligence (AI), the automatic recognition of individual has become an active area of research. And it has a wide application 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 convolution 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 Artificial Intelligence 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 Automatic video Interviews and the true personality scores from the facial expressions and self-reported questionnaires of real job applicants.*

Keywords: Big five, Convolutional Neural Network (CNN), Personality Computing, TensorFlow.

I. INTRODUCTION

Personality is determined as a set of characteristics which make an individual unique, and the study of personality considered as a central aim of psychology. One of the most influential and generally accepted personality theories is the big- five personality theory, which envelope five basic traits: Extraversion (sociable vs. shy), Agreeableness (friendly vs. uncooperative), Conscientiousness (organized vs. careless), Openness (insightful vs. unimaginative), and Neuroticism (neurotic vs. calm) to compose human personality. With the wide spread of social networks sites nowadays, Facebook becomes one of the most popular social networking services in the world. More than 1.3 billion users are daily active. As a consequence, Facebook plays a big role in people' normal life. Thus, the platform provides an ideal online platform for personality research and relative application. The information revealed through a personality assessment can be used in numerous applications. These include but not limited to, advertisements alignment, marketing campaigns adjustment, and supporting bloggers in narrowing down their target audiences based on community pre-detected personality traits. There are also many other applications that can take an advantage of personality recognition systems. For instance, a company selling guns can selectively show an advertisement describing their products as a sign of strength and force to extroverted people, while showing statistics of burglary and highlighting the apparent safety improvements to neurotic and anxious people. In recent years, the interest of the scientific community in personality recognition has grown very fast. Meanwhile, predicting user's personality through social networks is not an easy task. One of the critical factors that affect personality detection at the scale of social platforms is the predictive accuracy as an outcome of limited available training data. One of Facebook advantages (easy access to large amounts of personal data) introduce serious ethical challenges that have yet to be addressed in a pragmatic manner by the applicable legal and ethical guidelines. Several authors have looked at the Big Five personality traits of Facebook users. However, there is fewer work that analyze the usage of like button in the Facebook social platform in term of personality prediction. Likes can be used by Facebook users to endorse content such as status updates, comments, and photos, links shared by friends, Facebook pages, or external Web sites. Endorsements also result in users receiving updates on a given piece of content, such as comments on a liked status update. Likes were introduced by Facebook in February 2009. Likes can be used to categories users across a large variety of personal characteristics, political affluence, sexual orientation, or cultural ethnicity.

Industrial and organizational (I/O) psychologists have found that personality is a global predictor used in employment selection. Some employers use self-reported surveys to measure job applicants' personalities; however, job applicants

may lie when self-reporting personality traits to gain more job opportunities. 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. 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. 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. When using AVI, human raters find it cognitively challenging to correctly assess applicants' personality traits based on video images. Barrick *et al.* found that human raters were unable to accurately assess an applicant's personality simply by watching recorded-video interviews.

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. "AI is a branch of computer science that seeks to produce intelligent machines that respond in a manner similar to human intelligence", and it "aims to extend and augment human capacity and efficiency of mankind in tasks of remaking nature". Machine learning (ML) is a major approach for achieving AI, which "gives computers the ability to learn without being explicitly programmed". 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". In contrast to traditional ML, DL feature extraction is automated rather than manual.

II RELATED WORK

2.1 Problem Statement

Personality is considered as important criteria in explaining human behaviors. Recognizing one's personality has many advantages. It can be used in Deception detection, Recommendation systems and Sentimental analysis. The existing methods consist of various interviews or counseling by experts which is not economical. There are various other methods which can be used for personality recognition. The traditional methods like counseling and personal interviews by experts are expensive. The number of data entries used is less and it is static. Many a times, the manual interview process for hiring process may not provide a clear understanding of his personality.

2.2 Existing Method

- The traditional methods like counseling and personal interviews by experts are expensive.
- The number of data entries used is less and it is static.

In traditional personality computing, validating APR using manually labeled features from any possible detectable distal cues was quite complicated.

III. METHODOLOGY

3.1 Proposed Method

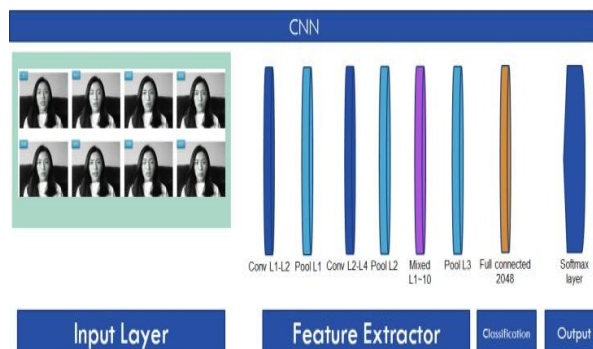


Figure 1: Proposed system architecture

Classification and tone analysis we will utilize machine learning algorithm like Naivey bayes, SVM or random forest. Using CNN algorithm and face landmarks we separate the component of the face which is the video. And successfully recognize the "big five" traits of an interviewee at an accuracy between 90.9% and 97.4%.

- 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.

CNN structure consisted of four convolutional layers, three pooling layers, ten mixed layers, a^A fully connected layer and a softmax layer as the output. In the neural network, the extracted features of the applicants' facial expressions were used as the inputs, and their self-assessed big five personality trait scores were used as the output. The fully connected network was built using the relationships between different nodes, as shown in Figure 1.

The input was represented by a grayscale image. Each of the four convolutional layers used 3×3 filter functions. The number of convolution filters increased from 32 in convolutional layer 1 to 64 in convolutional layer 2. Each convolutional layer was followed by a pooling layer. Both pooling layers (one average-pooling and two max- pooling) had a stride of 2×2 and the dropout rate was set to 0.1. The final fully connected layer included 2,048 neurons with dropouts of 0.4 and 0.5. The final layer of the proposed CNN was a softmax layer with 50 possible outputs (10 interval-scale classes from 1.1 to 6.0 that reflected the big five personality classifications). To prevent overfitting, we added dropout starting with a probability of 0.5 after the fully connected layers at the end of our convolutional network and then gradually reduced the dropout rate until the performance was maximized.

IV. ALGORITHM



Figure 2: What we see



What Computer Sees

Instead of the image, the computer sees an array of pixels. For example, if image size is 300 x 300. In this case, the size of the array will be 300x300x3. Where 300 is width, next 300 is height and 3 is RGB channel values. The computer is assigned a value from 0 to 255 to each of these numbers as shown in figure2. This value describes the intensity of the pixel at each point.

4.1 Convolution Layer

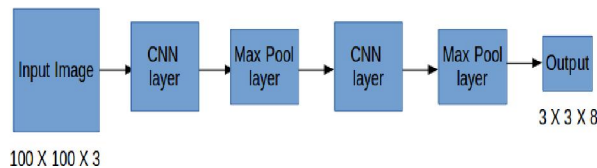


Figure 3: Formation of layers

The image is passed through a series of convolutional, nonlinear, pooling layers and fully connected layers, and then generates the output as shown in figure 3.

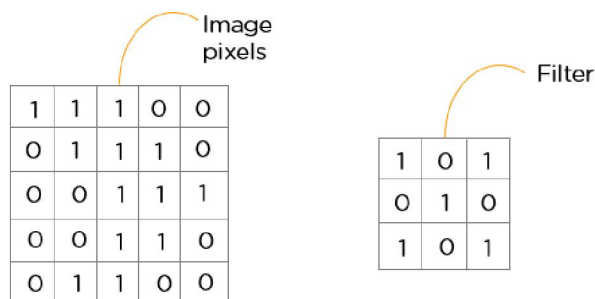


Figure 4: Convolution layer

This is the first step in the process of extracting valuable features from an image. A convolution layer has several filters that perform the convolution operation. Every image is considered as a matrix of pixel values. Consider the following 5x5 image whose pixel values are either 0 or 1. There's also a filter matrix with a dimension of 3x3. Slide the filter matrix over the image and compute the dot product to get the convolved feature matrix.

4.2 Pooling Layer

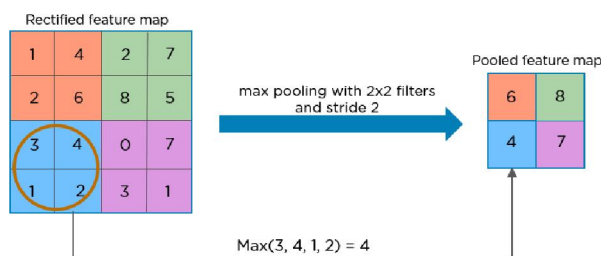


Figure 5: Pooling layer

Pooling is a down-sampling operation that reduces the dimensionality of the feature map. The rectified feature map now goes through a pooling layer to generate a pooled feature map. The pooling layer uses various filters to identify different parts of the image.

The next step in the process is called flattening. Flattening is used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The flattened matrix is fed as input to the fully connected layer to classify the image.

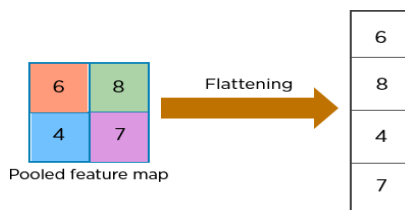
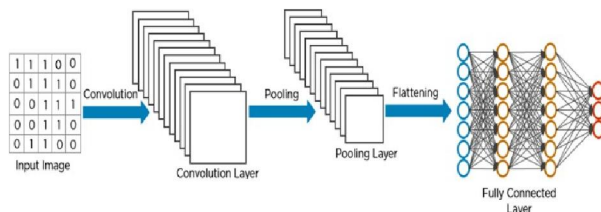


Figure 6: Flattening



4.3 Fully Connected Layer

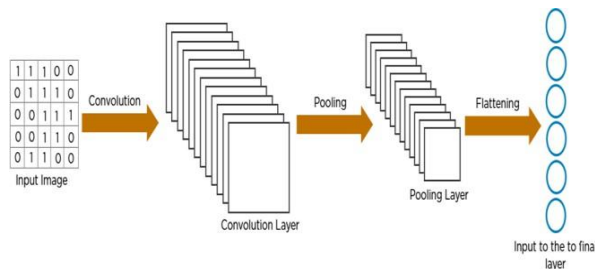


Figure 7: Fully connected layer

Here's how exactly CNN recognizes the pixels from the image are fed to the convolutional layer that performs the convolution operation, it results in a convolved map. The image is processed with multiple convolutions for locating the features.

Different pooling layers with various filters are used to identify specific parts of the image. The pooled feature map is flattened and fed to a fully connected layer to get the final output.

V. DATA PROCESSING

5.1 Data Collection

Data collection is the process of gathering and measuring information on variables of interest, in an established systematic fashion that enables one to answer stated research questions, test hypotheses, and evaluate outcomes. In order to establish the dataset in a real job interview context, we have developed AVI cloud-based software. The AVI server uses Google cloud storage and can receive recorded video prompts, generate interview scripts, transmit the video prompts from the interview, and receive the video responses. The content of the video responses can then be used to conduct algorithmic analyses, including audio and visual data analyses of the video responses. During the AVI, interviewees' answers can be recorded at one point in time but later reviewed by an algorithm, human raters, or both at another point in time.

We conducted an experiment with a non-profit human resources (HR) organization. The interview questions during the AVI were structured in a standard manner. All the applicants were provided with the same five questions, which were behaviourally oriented to assess the applicants' communication skills based on the job description. Each question was displayed on a new screen, and the audio of the text questions was automatically started when the applicants entered the screen. The questions were presented on-screen one at a time in sequence, and the applicants were given a maximum of 3 minutes to answer each question. The applicants could choose to skip to the next question within the 3-minute period. After 3 minutes, a newscreen automatically appeared with the next question. Including one practice trial, the entire video interview process lasted approximately 20 minutes.

5.2 Data Labelling

To collect the true ratings for the individual big five trait, we have used a 50-item international personality item pool (IPIP) inventory developed to measure the applicants' self-rated big five traits. Prior to participating in the AVI, all applicants were required to complete the IPIP survey online and informed that the survey results would be delivered to researchers only and that they would be irrelevant to the hiring recommendation. This procedure was conducted to reduce the effects of social desire, which may distort the self-rated personality traits in an effort to gain the job opportunity.

5.3 Feature Extraction

After data collected and labelling of data, feature will be extracted from the image. we trained our facial detection model based on OpenCV and Dlib while tracking 86 facial landmark points per frame, as shown in the below figure. To develop the feature extractor, we extracted the images frame by frame from our AVI dataset using FFmpeg.



Figure 8: Images Extracted from the video frames.

The width of all the images was normalized to 640 pixels, while the height of each image was determined by the pixel ratio of the vision device. We extracted the features of the 86 landmark points from each frame within a 5-second period from among all the AVI records for each applicant as shown in figure 8. To improve image classification and reduce background interference from hair and cosmetics, we converted all the images to grayscale. The test cases used in this experiment comprised more than 10,000 images.

V. RESULTS

The performance of any machine learning model strongly depends on the quality of the data used to train the model. When the data to train the model is very large, its size needs to be scaled down based on several factors. For this purpose, there are many methods used to reduce the dimensionality of the model. Some of these work in the case of linear while some work when there are non-linear relations between the features in the data. In this article, we are going to discuss locally-linear embedding which is an approach to non-linear dimensionality reduction with neighbourhood preserving embeddings of high dimensional data

VI. CONCLUSION

This model is based on identifying the personality of an individual using TensorFlow. The personality of a human plays a major role in his personal and professional life. Nowadays, many organizations have also started short listing the candidates based on their personality as this increase the efficiency of the work because the person is working in what he is good at than what he is forced to do.

ACKNOWLEDGMENTS

We would like to express our gratitude to our College, SJC Institute of technology our Guide prof. Vimala Devi.R mam and our project coordinator Aravind Tejas Chandra who have provided us with the opportunity to work on this project and given us support with guidance to make this project a success. We would also like to thank our teammates for their contribution and continued support and zeal towards this project. This project wouldn't be a success without them.

REFERENCES

- [1]. Sun A, Li Y, Lu G, 2018, "Facial expression recognition using optimized active regions", *Hum-Centric Comput Inf Sci* 8:33.
- [2]. McLarnon M. J. W and T. J. Schneider, 2019, "Faking it! Individual differences in types and degrees of faking behavior," *pp.* 88–95.
- [3]. Asabere N. Y and M. B. Michael, 2018, "Improving-socially-aware commendation accuracy through personality," *pp.* 351–361.
- [4]. O. Celiktutan and H. Gunes, 2017, "Automatic prediction of impressions in time and across varying context: personality, attractiveness and likeability," *pp.* 29–42.
- [5]. F. S. Brenner, T. M. Ortner, and D. Fay, 2016, "Asynchronous video interviewing as a new technology in personnel selection: the applicant's point of view," *pp.* 1–11.
- [6]. M. I. Jordan and T. M. Mitchell, 2015, "Machine learning: trends, perspectives, and prospects," *pp.* 255–260.
- [7]. R. Petrican, A. Todorov, and C. Grady, "Personality at face value: facial appearance predicts self and other personality judgments among strangers and spouses," *J. Nonverbal Behavior*, vol. 38, no. 2, pp. 259–277, Jan. 2014.

- [8]. S. Nestler and M. D. Back, 2013, "Applications and extensions of the lens model to understand interpersonal judgments at zero acquaintance," pp. 374– 379.
- [9]. "Escalante HJ, Junior JJ, 2018, "Explaining first impressions: modeling, recognizing, and explaining with the advent of artificial intelligence (AI) apparent personality from videos". arXiv preprint arXiv :18020 0745. "
- [10]. "Sun A, Li Y, Lu G, 2018, "Facial expression recognition using optimized active regions", Hum-Centric Comput Inf Sci 8:33.