Human Sales Ability Estimation Based on Interview Video Analysis

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***Abstract*—In this paper, we introduce our proposed method for estimating the potential sales ability of a person based on interview analysis. A deep learning model was built and trained to estimate the major personality traits according to Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism in the (OCEAN) model. The model utilizes Convolutional Neural Networks (CNNs) and Long Sort-Term Memory (LSTMs) to extract and learn features from the sequence of the frames for each video. Base knowledge has been built to define the decision rules for classifying the participants depending on their personality analysis and to give the final classification score. The decision rules depend on the relation between the Big Five Factors that describe salesmen represented by high levels of (Extraversion, Conscientiousness, and Openness) and low levels of (Neuroticism and Agreeableness). We collected our dataset by building our website to let participants record self-introduction videos while answering customized questions for our task. The model was trained on two datasets: the Computer Vision and Pattern Recognition (CVPR) First Impressions V2 was used to train the model to be able to estimate personality traits and our dataset that were used to fine-tune the model to our task and capture the potentials of a salesman. The proposed method has been tested on a variety of samples including video samples for real sales managers and achieved good results in classifying them.**

I. INTRODUCTION

Sales companies receive many requests when there is an opportunity to work for them and usually it is difficult to process and analyze all requests and conduct interviews with all applicants. Hence, a tool that helps to sort applicants and nominate a selection of them for the interview to get the job is an innovative solution for companies. A deep learning model is proposed that analyzes personal introduction videos of applicants, extracts their personality traits, and uses them to classify applicants who have qualifications to work in the field of sales.

Nowadays soft skills and personality play a crucial part in jobs that depend on interaction with clients and negotiating with them, having a deep learning tool that will estimate these kinds of characteristics can be a major help in choosing the suitable applicant for the job, simplifying the process of selection and reduce time-consuming for hiring.

Since we need an automated tool that can imitate human decisions, here comes the power of using a deep learning model to solve this task, and proven by many researches how deep learning techniques like CNNs achieve great results in analyzing and extracting features from videos and images.

The scientific novelty of the paper covers the following:

- We propose expert-based knowledge for sales managers classification.
- We developed a novel method for people classification about the sales manager position based on the video interview analysis.

The rest of the paper is organized as follows. Section II represents the overview of previous studies about methods for personality estimation. Section III shows the used datasets and explains the method of collecting the data. Section IV shows the proposed method including pre-processing steps, estimating the apparent personality traits, the classification system, and the rules for building the base knowledge. Section V presents the experiments for testing the proposed method. Section VI concludes our work and future insight.

II. PREVIOUS RESEARCH OVERVIEW

Many studies talked about personality analysis and the relationship between facial traits, emotions and reactions with describing the general character of a person and how these traits can be related with potential skills required for a certain type of jobs. Researches show that physical appearance and the friendly, attractive and neat sales manager can affect his credibility [7]. The authors of [8] introduced the OCEAN model for personality analysis where each person has a given score on each dimension (openness, conscientiousness, extraversion, agreeableness and neuroticism). The characteristics

TABLE I. CHARACTERISTICS DESCRIBED BY THE OCEAN MODEL

Dimension	Low score	High score
Openness	Practical, conventional and prefers routine	Curious and independent
Conscientiousness	Careless and disorganized	Hardworking and dependable
Extraversion	Reserved and Quiet	Outgoing and adventure-seeking
Agreeableness	Suspicious and uncooperative	Supportive and empathetic
Neuroticism	Calm and secure	Vulnerable to unpleasant feelings

TABLE II. THE RESULTS OF PREVIOUS RESEARCH WITH THE METHODS USED

Author	Modality	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness	Mean accuracy
Bekhouche et al [1]	Visual	0.9103	0.9137	0.9155	0.9082	0.9100	0.9115
Ventura et al [2]	Visual	0.910	0.911	0.909	0.905	0.909	0.909
Gucluturk et al [3]	Audiovisual	0.9101	0.9137	0.9107	0.9089	0.9110	0.9109
Zhang et al [4]	Audiovisual	0.9130	0.9166	0.9133	0.9100	0.9123	0.9130
Li, et al [5]	Multimodal	0.9177	0.9218	0.9202	0.9146	0.9195	0.9188
Aslan et al [6]	Multimodal	0.9189	0.9214	0.9208	0.9162	0.9166	0.9188

of the OCEAN model for each trait have been described based on the score by [9] as shown in Table I.

Several solutions have been presented for personality analysis based on a video. The third-place winners of the ChaLearn First Impressions Challenge presented a deep learning model without any feature extraction or face recognition techniques. They used a deep residual network consisting of 17 stacked convolutional layers (with a residual connection every two layers) followed by average and max pooling and finally a fully connected layer to give the final prediction. The residual model uses both visual and audio features to estimate the personality traits [3].

The winners of the ChaLearn First Impressions Challenge presented their method for estimating apparent personality traits by building a Deep Bimodal Regression(DBR) that processes both the audio and video frames in order to give the final prediction. Their method can be divided into two parts. Extracting visual features using Descriptor Aggregation Network (DAN), which is a modification on the CNN architecture by removing the fully connected layers and adding both average and max pooled layers to give a final 512-d feature vector. Extracting audio features by using a regression model consists of fully connected layers to predict personality traits. Finally, the output of the model is the average of the visual and audio predictions [4].

The authors of [10] proposed a method for personality recognition based on extracting key points from the participant's face, then using dimensionality reduction and feeding these points into a five-dimensional prediction model depending on Support Vector Regression (SVR).

A method for predicting the personality traits was introduced by [1]. They proposed cropping the face from each video and stacking them all together, then training a model to extract facial features and predict personality scores in each dimension. The proposed method depends on extracting texture features from the sequence of frames then feeding them to 5 SVR to estimate the personality traits.

The authors of [11] proposed a machine learning model using Convolutional Neural Networks, to perform automatic personality recognition based on asynchronous video interviews. They collected a custom dataset by using an end-to-end AI interviewing system. Their proposed method is based on tracking key points on the face in order to detect facial expressions and movements and use these features to estimate the personality cues.

The authors of [2] interpreted why CNN models do a great job estimating the apparent personality from a video. Their study proves that most of the visual features provided by facial expression and facial regions like mouth, nose and eyes are the significant parts analyzed by the model. They trained a CNN model with the same architecture proposed by [4] but instead of using visual and audio features, they trained the model on extracted faces only. Their results show that using only faces can achieve good results estimating the personality traits.

A deep Classification-Regression Network (CR-Net) is presented by [5] for predicting the personality traits. The proposed multimodal model takes into account global cues (the whole frame), local cues (faces) and audio-text input. The proposed model is trained on the ChaLearn First Impressions dataset and achieves the state-of-the-art results with mean accuracy on the test set (0.9188).

A Multimodal method for estimating personality cues is presented by [6]. They proposed a method that uses Convolutional Neural Network (CNN) for feature extraction followed by Long Short-Term Memory (LSTM) to recognize the apparent personality. They also make a fusion model from four sub-networks for feature-based recognition (ambient, facial, audio, and transcription).

According to previous research, recognizing and analyzing personality traits based on videos and described by the OCEAN model can be done using deep learning techniques like CNN and LSTM.

As shown in Table II that summarizes the results of many research studies and shows the modality used by each research study, we conclude that using only visual features can achieve good results and is close to the state-of-the-art. According to that, and since our task is to classify people for sales positions not to develop a new method for estimating personality traits we propose a method for estimating personality cues (which is only the first part of our proposed method) using only visual modality, not to mention that using only images makes the training process faster compared to using multimodal methods. None of the previous studies solved our task of estimating sales potential based on personality analysis. In this paper we propose our method for estimating potential salesmen traits based on apparent personality recognition and finding cues that define participants qualified to work in sales.

III. DATA COLLECTION

This study used two datasets to estimate the personality traits and classify the participants qualified for sales positions.

Fig. 1. Our website for collecting data

1) First Impressions V2 (CVPR17): The dataset consists of 10,000 video samples of people speaking in English while facing the camera [12]. The videos were sampled from YouTube with high resolution (1080x720). The average duration is 15s with an average frame rate per second of 30 fps. Amazon Mechanical Turk (AMT) was utilized to generate the ground truth for each video. The ground truth represents personality traits according to the Five Factor Model (Big Five Model). As a result, each video has ground truth labels for these five dimensions (openness, conscientiousness, extraversion, agreeableness, and neuroticism) each of which is represented by a value between 0 and 1.

2) Our own collected dataset: In this study, we built a website to collect data for our task as shown in Fig. 1. The website was built using Hypertext Markup Language (HTML), Cascading Style Sheets (CSS), and JavaScript [13]. The website allows the participants to record a self-introduction video using their camera. When the participants enter the site it will ask them to access their device camera. The website has all the instructions needed for recording the video and how to swipe through the questions. The website is considered the easiest, and most convenient way for collecting data, since it can be accessed from all devices and all operating systems. Participants only need an internet connection and a web browser. We asked participants to record a video introducing themselves while facing the camera. The participants have to answer the following questions: (1) Introduce yourself, such as your name, age, speciality, and a few pieces of information that describe you; (2) What skills do you have that will help you work in a potential company, where would you like to go to work? (3) Do you like to do sales? (4) Why do you want to do sales today? (5) What achievements are you proud of over the past 3 years?

After self-introduction, the participants were required to complete the International Personality Item Pool 50-item (IPIP-50) personality test to get the ground truth [14]. The final dataset consists of 112 clips sampled from the participants' videos (28 samples) with an average duration of 15 seconds.

The collected dataset has a variety of samples and the majority of the participants were students who had different personality scores and also different sales backgrounds. As we mentioned before we have 112 samples from 28 participants to ensure that the model will train normally with no imbalance in any category of samples. We make sure to sample 4 video clips from each video participant and make sure that these samples are disturbed in the following ratio 2:1:1 to the train, validation, and test sets so the model trains normally with no imbalance to any group of samples or dominant features against others.

We used an automated method represented by the website we built that allows us to collect data from participants. We used in this study only the quality collected samples where the participant's face is clear and visible in the video. Also, we used the samples where the participants answered the personality test we provided and agreed to the terms for using their videos in this study.

IV. Proposed Method

A. General description

The proposed method for solving the task of classifying people qualified for sales positions depending on video interviews is shown in Fig. 2. The pipeline for our method is as follows: First, we sampled each video input into frames, applying a face detection method to detect the face from each frame and crop it out, then applying pre-processing techniques like resizing and rescaling to make the input in the desired form for our model. Second, we used pre-trained CNNs to extract features from the stack of the input frames. Third, we estimated personality traits by feeding the extracted features into stacked LSTM layers followed by Dense layers. Fourth, we trained our model on the dataset we collected for the potential sales estimation. Finally, we built a knowledge base to define the rules to give the final classification score.

B. Data pre-processing

Our proposed method for estimating the Big Five Factors depends only on visual modality. Proceeding from that, we sampled the videos frame by frame, then we used 3D Dense Face Alignment (3DDFAV2) to detect the face in each frame and crop it out [15]. Since the videos are high quality with an average of 30 fps, that will produce 450 frames per video, and taking all the frames for each video will be computationally expensive to train the model. So, we sampled out only 60 frames from each video and resized each frame to 64x64x3 pixels. We also applied data rescaling to change the value of the pixels from [0-255] to the range [0-1]. In addition to applying the same previous steps for pre-processing our dataset, we calculated the ground truth for the collected videos by following the scoring system for each question in the IPIP-50 test.

C. Personality traits estimation

We used Convolutional Neural Networks with Long Short-Term Memory to estimate the personality traits. CNNs are

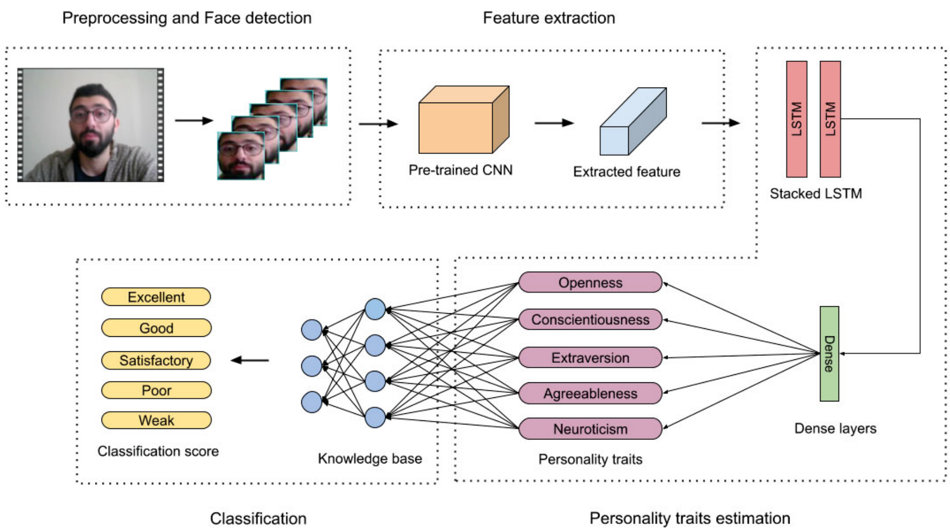

Fig. 2. The architecture of the proposed method

considered the core of deep learning networks that deal with images and are useful to solve computer vision tasks like classification and regression. Long Short-Term Memory is a type of Recurrent Neural Network that can deal with sequenced data like videos, and learn the dependencies through the whole sequence of the data. This makes it suitable for our task. Convolutional Neural Networks do a great job by extracting features from photos and they are also suitable for many computer vision tasks. We used Keras Applications for Pre-trained CNNs as a perfect start for our models, since it was trained before on a huge dataset and learned many useful features for computer vision tasks [16].

We tried multiple pre-trained CNN models as spatial feature extractors. We attempted to freeze the weights of the first layers (because these layers already learned the basic feature that could be extracted for a computer vision task). Then we fine-tuned the rest of the layers to fit our task, and fed the extracted features to LSTM layers. This was followed by Dense layers to get the final estimation for personality traits. The purpose of using Long Short-Term Memory is to make use of the temporal data between video frames and to learn features related to the facial movements which can be represented through the frame sequence [17] [18]. To measure the accuracy of the model, we used the mean accuracy that is defined by the equation

$$E = \frac{1}{5N} \sum_{j=1}^{5} \sum_{i=1}^{N} 1 - |p_{i,j} - t_{i,j}| \tag{1}$$

where $p_{i,j}$ – is the predicted score, $t_{i,j}$ – the ground truth score, and N – the number of samples.

The model's architecture for apparent personality estimation is shown in Fig. 3. The input of the model is stacked of frames for each sample represented by a tensor (None, 60, 64, 64, 3) fed to a pre-trained CNN to extract facial features followed by stacked LSTM layers and finally Dense layers and the model's output is a tensor (None, 5) representing the personality traits. The results for training multiple models with the mean accuracy (1) achieved by each model are shown in Table III.

TABLE III. RESULTS FOR TRAINING MULTIPLE MODELS

Model	LSTM	Dense	Loss(MSE)	Mean-acc
VGG16	Two layers, 64 units	One layer, 32 units	0.01592	0.8904
VGG19	Two layers, 64 units	One layer, 32 units	0.01613	0.8826
ResNet50V2	Two layers, 128 units	One layer, 64 units	0.01577	0.8852
ResNet101V2	Two layers, 128 units	One layer, 64 units	0.01542	0.9002
EfficientNetB1	One layer, 512 units	One layer, 256 units	0.0152	0.9022
EfficientNetB2	Two layers, 64 units	One layer, 32 units	0.01446	0.9042
EfficientNetB3	Two layers, 64 units	One layer, 32 units	0.01512	0.9025
EfficientNetB4	Two layers, 128 units	One layer, 64 units	0.0155	0.9012
EfficientNetB5	One layer, 1024 units	One layer, 256 units	0.0155	0.9009

D. *Fine-tuning the model*

To solve the task of classifying people for sales positions depending on their personality traits, and since we have a small dataset (112 samples), we did a second phase of training by using the best model we trained on the CVPR V2 First Impressions (which is EfficientNetB2 as shown in Table III) as a pre-trained model and fine-tuned it to our data. The

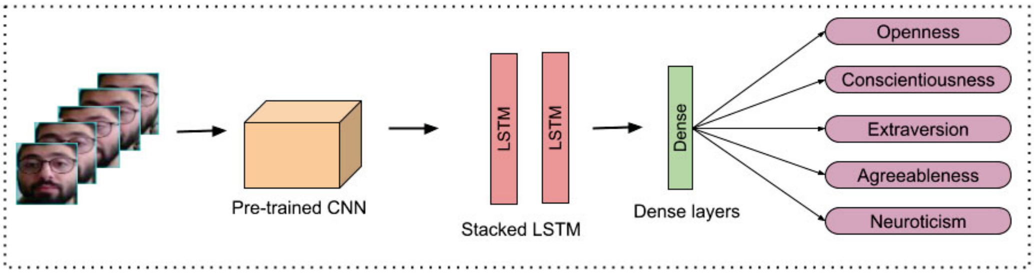

Fig. 3. The architecture for apparent personality estimation

weights of the pre-trained model are considered a perfect start to fine-tuning the model for our dataset since it has already learned the important features and characteristics to predict personality traits. We divided our dataset into 3 parts: training (56 samples), validation (28 samples), and testing (28 samples). The final model achieved very good results on the test set with a mean accuracy = 0.9084. Our proposed method for rating the potentials of individuals for a salesman position is shown in Fig. 2.

E. Classification system

According to previous research, there is a relationship-between personality traits and a person's potential for a sales position. Given that sales managers in general have high levels of Extraversion, Conscientiousness, and Openness as well as low levels of Neuroticism and Agreeableness [19], we built knowledge-based system for classifying a person by sales ability based on top 5 personality dimensions. The idea is to divide each personality dimension into multiple ranges and give each range a score, then for each participant we average their score over the five dimensions to get the final classification score. To define the ranges of each dimension, we studied the probability distribution that fits each personality trait and then divided it into 10 ranges depending on the percentile principle. As a result, a participant has an integer score value in the range [1,10] for each dimension depending on which range their score falls in. Since the high levels of extraversion, conscientiousness, and openness describe the potential of a salesman, the classification score on these dimensions represents a positive direction with the personality traits. In other words, a high personality score equals a high classification score on these dimensions. At the same time, the levels of neuroticism and agreeableness represent the negative direction with personality traits. This means a low personality score equals a high classification score on these dimensions. The thresholds that define the ranges on each dimension are shown in Table IV, where Fig. 4 shows the distribution of each dimension.

V. Experiments

The proposed method has been tested on test set represented by 28 samples and we have also tested our method on 3 more samples for people who work in sales and recorded video interviews answering our custom questions. Data has a variety of genders (11 females 39.29% and 17 males 60.71%) and races (17.85% Syrians and 82.14% Russians). The participants are from two countries (Russia and Syria) and also from different regions (Moscow, Saint-Petersburg, Damascus, Lattakia, and Aleppo). The results for classification are shown in Fig. 5. For each sample, the model estimates the big 5 personality traits then depending on the prediction results and according to the decision rules in the base knowledge, a classification score for the person's potential in sales in the range [1,10] is given. As we can see, the model gives high classification scores for the sales managers which proves that our knowledge base and our proposed method give a good estimation of the sales potential.

To prove that the decision rules we established for classifying people depending on their potential in sales and to check if the classification system we created is doing a reasonable

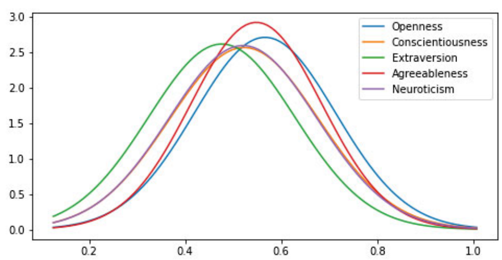

Fig. 4. The probability distribution of the CVPR V2 dataset on each trait

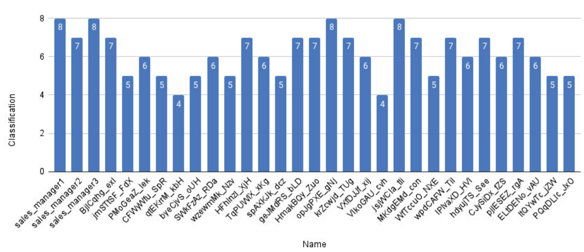

Fig. 5. The classification results

TABLE IV. CORRESPONDENCE OF TOP 5 CHARACTERISTICS AND SALES MANAGER SCORE

Classification	1	2	3	4	5	6	7	8	9	10
Extraversion	[0, 0.28)	[0.28,0.35)	[0.35,0.40)	[0.40,0.44)	[0.44,0.48)	[0.48,0.51)	[0.51,0.56)	[0.56,0.60)	[0.60,0.67)	[0.67,1]
Openness	[0,0.38)	[0.38,0.44)	[0.44,0.49)	[0.49,0.53)	[0.53,0.57)	[0.57,0.60)	[0.60,0.64)	[0.64,0.69)	[0.69,0.75)	[0.75,1]
Conscientiousness	[0,0.32)	[0.32,0.39)	[0.39,0.44)	[0.44,0.48)	[0.48,0.52)	[0.52,0.56)	[0.56,0.60)	[0.60,0.65)	[0.65,0.72)	[0.72,1]
Agreeableness	[0.63,1]	[0.57,0.63)	[0.52,0.57)	[0.49,0.52)	[0.45,0.49)	[0.42,0.45)	[0.38,0.42)	[0.34,0.38)	[0.28,0.34)	[0,0.28)
Neuroticism	[0.68,1]	[0.61,0.68)	[0.56,0.61)	[0.52,0.56)	[0.48,0.52)	[0.44,0.48)	[0.40,0.44)	[0.35,0.40)	[0.28,0.35)	[0,0.28)

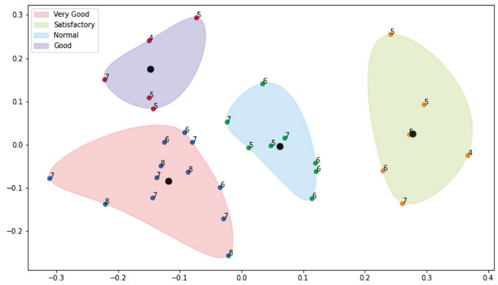

Fig. 6. The clustering results divided into 4 groups

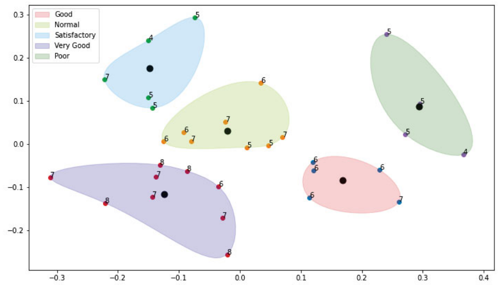

Fig. 7. The clustering results divided into 5 groups

job, we clustered the samples we have using the K-means clustering algorithm. After estimating the personality traits for each sample we used K-means to cluster these samples. We applied dimensionality reduction to transfer the data into 2D space using Principal Component Analysis (PCA), then we clustered the samples into 4 and 5 clusters as illustrated in Fig. 6 and Fig. 7. As shown by clustering results, each group of samples that have close classification scores belongs to the same cluster (while taking into account the possibility of errors represented by anomalies) which also proves that the decision rules we established are valid and reasonable for classifying people to qualify for sales positions depending on a video interview.

VI. CONCLUSION

In this paper, we introduced our method for classifying people according to their potential in sales taking into account estimating their personality traits and using it to make the classification decision. We built a deep learning model that solves the task of estimating personality traits measured according to the OCEAN model and uses these traits to build a knowledge base that can decide how good a person could be for a sales position. We tested our method on a dataset gathered for our task and the proposed model gives good results in classifying the samples and estimating qualified people for a sales position.

This study can be considered the seed for many other studies in the field of automatic and semi-hiring systems. It provides a helping tool for large companies to select a suitable person for a job, and it also provides valuable information about the participant's personality that can be critical in many jobs.

Future work should focus on expanding our work by collecting large datasets for people from many professions and training the model on these data to build a more general and global view of how can personality traits and soft skills estimation helps spot potential candidates for a specific job.

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