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Apparent Personality Prediction: Psychoanalytic and Technological Aspects

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Abstract - *This report investigates the association of personality traits with visual attributes. We propose a personality detection system based on any textual, auditory, or visual data acquired from the user and process it to give real-time personality information. This system can further be developed into a mobile app, making it easier for users to detect personalities. Through a mobile app, the study group can be increased to a vast population. The functions developed in the process can be developed into a library, making it easier to integrate the system into various technologies. The data processed may be used further for application into various use cases.*

Key Words: **facial feature extraction, facial landmarks,**

1.INTRODUCTION

According to the American Psychological Association, [1] personality refers to individual differences in characteristic patterns of thinking, feeling, and behaving. The study of personality focuses on two broad areas: Understanding individual differences in particular personality characteristics, such as sociability or irritability. The other is understanding how the various parts of a person come together as a whole. There are two aspects to any personality detection system, the psychoanalytic and the technological. We will focus on the technological aspect of the system in this paper.

1.1 The OCEAN Model

The Big Five Model, also known as the Five-Factor Model, is the most widely accepted personality theory held by psychologists today. The theory states that personality can be boiled down to five core factors, known by the acronym CANOE or OCEAN:

Table -1: OCEAN model

	OCEAN Model
Conscientiousness	impulsive, disorganized vs. disciplined, careful
Agreeableness	suspicious, uncooperative vs. trusting, helpful
Neuroticism	calm, confident vs. anxious, pessimistic
Openness to Experience	prefers routine, practical vs. imaginative, spontaneous
Extraversion	reserved, thoughtful vs. sociable, fun-loving

Unlike other trait theories that sort individuals into binary categories (i.e., introvert or extrovert), the Big Five Model asserts that each personality trait is a spectrum. Therefore, individuals are ranked on a scale between the two extreme ends. By ranking individuals on each of these traits, it is possible to measure individual personality differences effectively.

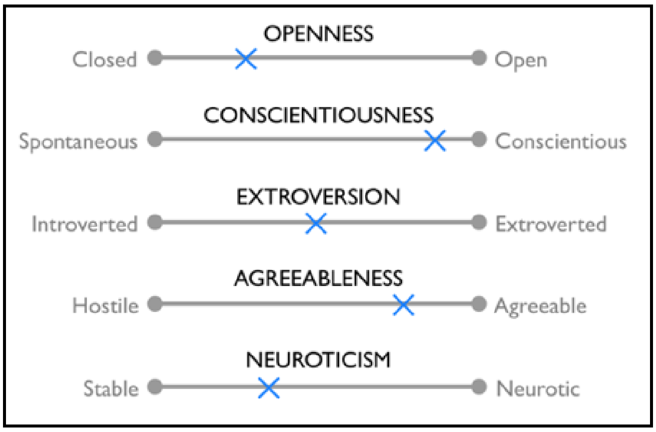

Fig -1: Spectrum nature of OCEAN Model

2. RELATED WORK

There needs to be a relationship set between the facial features of a person and their personality trait. Xue et al. [2] proposed investigating this relationship. A facial image-based personality classification was used. Given a static facial image, the proposed method extracts geometric facial features to define attributes, which are then used to estimate the corresponding personality traits. First, landmark detection methods are applied to a facial image to detect 77 landmarks automatically. After that, the distance, angular, and area-based attributes are calculated and chosen to form the feature vector used to represent the image. Finally, a classifier is trained using the feature vectors to recognize personality traits.

An interesting model to detect these facial landmarks can be found in the works of Yury Kartynnik et al. [3] that explores an end-to-end neural network for the creation of dense mesh models on faces captured from video/images for AR purposes. A mesh prediction model (Facemesh model) is trained that identifies 468 vertices to create a face mesh. The result is a face mesh with 468 facial vertices with x, y, and z coordinates. This model is repurposed for the requirements of this paper.

3. IMPLEMENTATION

The proposed method involves getting input in the form of an image or video (images are extracted from frames), extracting geometric facial features, defining attributes using them, and predicting corresponding personality traits.

3.1 Assumptions and Dependencies

The determined personality through this system is assumed to be the person's actual personality, while it is only the person's apparent personality. Apparent personality is the person's personality at first glance based on various physical characteristics and social assumptions. The determined personality may differ from the person's actual personality.

3.2 Dataset

Only a few datasets present online provide both the image of the user and its OCEAN personality score. Also, there is no standard dataset for facial attribute-based personality prediction. So, we created a facial attribute dataset on our own. We used the First Impressions V2 (CVPR'17) dataset for our purposes.

The first impressions data collection comprises 10,000 clips (average time 15 seconds) taken from over 3,000 separate YouTube high-definition (HD) recordings of people facing and speaking in English to a camera. With a 3:1:1 ratio, the films are divided into training, validation, and test sets. People in the videos are of various genders, ages, nationalities, and ethnicities.[4]

The dataset contained videos and corresponding annotations of the Big Five traits. Images of people were captured from the videos, and the Facemesh model returned the respective facial landmarks. These facial landmarks, in addition to the annotations, were what were used for training the model.

3.3 Proposed Method

First, the Facemesh model detects the 468 facial vertices from a static facial image which are then pixel normalized according to the frame size. Then 28 distance, angular, and area-based facial attributes are calculated from these vertices. Finally, a classifier is trained based on the attributes and the corresponding personality scores from the First Impressions dataset. The result is a system that takes a static image input, extracts and calculates the facial attributes, and predicts its personality score.

Table -2: Facial attributes calculated

Attribute Name	Landmark Indices
eyebrow separation	55,285
right eyebrow length	276,285
left eyebrow length	70,55
eye separation	463,243

4. EXPERIMENTAL RESULTS

Various classifiers were trained with both one-factor and two-factor analyses. The results found are mentioned below.

4.1 One Factor Analysis

A correlation between the calculated facial attribute values and each personality trait of the OCEAN model was assumed. Various models were trained using the training dataset, and the r^2 score of its predicted test values was recorded. Random Forest Regression was found to have the most positive r^2 score, i.e., least error. Many models presented with negative r^2 scores, meaning that they failed to fit the training data.

	SVR()	DecisionTreeRegressor()	RandomForestRegressor()	AdaBoostRegressor()
extraversion	0.077806051	-0.78025668	0.11113273	0.065428518
neuroticism	0.075996167	-0.756276011	0.12255995	0.034025399
agreeableness	0.071343552	-0.935929547	0.063193771	0.077151229
conscientiousness	0.09169954	-1.133610125	0.247604932	0.12354503
openness	0.039236491	-1.286885108	0.052536198	-0.010106286

Fig -2: r^2 score of one-factor models

4.2 Two Factor Analysis

A correlation between the calculated facial attribute values and every possible set of two personality traits of the OCEAN model was assumed. Various models were trained using the training dataset, and the r^2 score of its predicted test values was recorded. Random Forest Regression was found to have the most positive r^2 score here too. Only Random Forest Regression and Linear Regression performed well here. Many models were skipped as they do not support multiple outputs.

	DecisionTreeRegressor()	RandomForestRegressor()	LassoLars()	LinearRegression()
extraversion/neuroticism	-1.080271383	0.115332731	-0.005366776	0.123566513
extraversion/agreeableness	-0.654836504	0.064714898	-0.003512652	0.104635519
extraversion/conscientiousness	-0.768980991	0.172236307	-0.005343888	0.130288684
extraversion/openness	-1.039529952	0.073861842	-0.00524043	0.033437372
neuroticism/agreeableness	-0.751784008	0.109915856	-0.002894322	0.124481028
neuroticism/conscientiousness	-1.062670136	0.193967224	-0.004725558	0.150134192
neuroticism/openness	-0.6686566	0.068580036	-0.004622099	0.053282881
agreeableness/conscientiousness	-0.671888401	0.152427972	-0.002871434	0.131203198
agreeableness/openness	-1.13390584	0.08061299	-0.002767975	0.034351887
conscientiousness/openness	-0.755012476	0.181393267	-0.004599211	0.060005051

Fig -3: r^2 score of two-factor models

4.3 Discussion

Human personality traits are affected by genetics and environment, and the heritability of the five personality traits is up to 57% [5]. Hence, the personality trait values predicted here are only the apparent personality. This personality is further affected by a person's past experiences, of which we have no contextual information. Thus, the use of the word "apparent". Therefore, predicting a person's actual personality becomes unfeasible in terms of the environmental and contextual data relating to a person's life.

Though the personality predicted is apparent, a correlation between the geometrical features of a person's face and his/her personality traits has been set owing to the experimental results found using the ChaLearn's First Impressions Dataset. It can be observed that the one-factor analysis of the data has given satisfactory results. Also, it can be observed that the two-factor analysis of specific combinations of personality traits gave more accuracy than certain other combinations.

5. CONCLUSION

This paper works on finding a relation between the facial attributes and the personality traits of a person. First, the facial images of people are captured, then facial landmarking is done using the Facemesh model. The extracted coordinates are used to calculate various facial attributes, such as eyebrow separation. Several regressors are trained, and the results from these models show a correlation between these values. A Random Forest Regressor was found to predict the personality with the slightest error. The results found from this project were satisfactory enough and at par with the results of the base paper. Therefore, it is safe to say that developing a more accurate automatic personality prediction system using facial features is possible.

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