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Model for Automatic Detection of the Big Five Personality Traits Through Facial Images

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Abstract: **This paper presents a model based on deep learning for the automatic prediction of the big five personality traits: Extraversion, Agreeableness, Responsibility, Emotional Stability and Openness to Experience. For the development of the model a set of five neural networks was used, three of them built from an Inception Resnet V2 network, a network already trained to detect the facial area of a portrait provided by the DeepFace library and a FeedForward network built in this study using the results of the previous ones. To train these networks, a dataset of 13026 facial images was generated from a set of videos provided by Chalearn [1]. The model achieved an interesting accuracy rate, 64% was obtained by averaging the 5 factors (Extraversion = 64%, Agreeableness = 72%, Responsibility = 61%, Emotional Stability = 63% and Openness to Experience = 62%). Compared to other studies, the model presented in this article has several advantages: (1) it generated a new dataset for the study (2) it supports facial images with low quality, non-static and background and (3) the trained model can work with a large pixel size (299,299,3).**

Keywords**:** Affective computing, big five model, deep learning, machine learning, personality prediction, personality traits.

I. Introduction

Automatic personality detection is one of the three main problems of computerized personality analysis, together with automatic perception and synthesis [2], it is highly relevant because the personality of an individual is rooted in all aspects of his life and can influence all decisions and activities that a person makes [3]. Personality describes the way in which an individual interacts with the outside world and the surrounding environment, it also helps us to understand how people think and feel and influences their motivations, preferences, emotions or even their own health.

Since the beginning of humanity, the detection of personality traits was present, during the times of ancient Greece appeared an idea about how the personality of each person worked, an example is in the theory of the four humors of Hippocrates and later improved by Galen who proposed the four temperaments, these could describe the behavior of a person based on a body fluid [4].

Due to the complexity of describing correctly the personality because of its large scope of characteristics, artificial intelligence uses every time new techniques or tools to solve this problem, on the other hand psychologists looked for a set of dimensions or general traits that can describe the personality, this type of set is called factorial model of personality traits, this type of model is able to describe stable patterns of behavior that persist over long periods of time [5], in the study of [6] the first factor model was developed systematically using questionnaires to a massive group of people, but it is in [7] where it was stated that factor analysis is the best method to study the association of individual test variables with personality traits.

Nowadays people have started to question the detection of personality traits through the analysis of their behavior, some researchers consider it as an old manual technique that requires a lot of time and resources, showing itself as a tedious activity that expends a lot of human effort to apply it, besides it is prone to biases and prejudices related to human nature, therefore it is necessary to search for new techniques to automate the detection of personality traits.

According to [8], psychologists have discovered that body language, as well as facial expressions, body postures, arm gestures or gaze are related to the personality of individuals, and especially in this era it is popular for people to take pictures or selfies, because of this an easy image can be taken as an easy and quickly accessible source for the detection of personality traits.

Several studies are applying Artificial Intelligence methods to automate many problems in the world, it has even been shown that its use presents superior performance in solving many difficult image classification problems [9], therefore, it is necessary to further investigate among these novel tools in order to obtain better results in the study.

In summary, improving the automatic detection of personality traits would generate a good impact on society, support related research and allow people to know more about their own behavior and improve their quality of life, it would also open new possibilities in technology, recommendation services would improve, since, by knowing better the personality, the recommendation would be closer to the user's expectations.

The objective of the research is to design a machine learning model capable of detecting the personality traits of a person using the InceptionResnetV2 residual neural network as a basis.

The rest of the content of the article is structured as follows, section II describes the research done so far related to the automatic detection of personality traits indicating possible improvements and opportunities for future studies, of which the present research seeks to improve, section III explains the design of the model proposed as the objective of the study, the construction of a new data set to train the model and its architecture, section IV describes the results of the research and the interpretation given in this study, finally in section V we discuss these results comparing them with other related works, also in the conclusions and future work we indicate the opportunities for improvement of this type of research.

II. RELATED WORK

A. Factor models of personality traits

There are several factorial models of which the most widely used are the Big Five trait model and Eysenck's PEN model, which will be described below:

1) The Big Five trait model

In his work, [10] has reduced personality traits to five dimensions (Neuroticism, Extraversion, Openness to experience, Agreeableness, and Conscientiousness) and has been employed since the 1980s by psychologists in personality research.

The study by [11] described the Big Five trait model as a compliance model, which assumes that a basic strength lies within an individual and that the strength drives him throughout life to realize his potential his talents and inherent abilities, these specific traits change only through logical maturation and not learning.

In [12] they introduced NEO the Personality Inventory which consisted of 189 items to measure the big five personality traits using six facet scales for each, four years later they introduced the NEO-FFI as a short version as well as new norms appropriate for use with college-aged adults, the study used a trait-based data set obtained through a NEO-FFI survey.

2) Eysenck's PEN Model

Eysenck also developed a factorial PEN model containing three personality traits (Psychoticism, Extraversion and Neuroticism) [10], this model incorporates two important principles of personality research which are aggregation and state-trait distinction, another important feature to mention in this model is that it is biologically based, it includes thresholds of cortical arousal and activation in the sympathetic nervous system or visceral brain [13].

B. Automatic detection of personality traits through facial images

1) Models using artificial neural networks.

In the literature review, it has been observed that it is difficult to obtain datasets of facial images related to their personality characteristics, because this information is generally used for private purposes and requires confirmation from each user before it can be used in research. To overcome this obstacle, some studies have set out to generate their own datasets [13-14], others extracted images from a set of videos [15-16], and only one study was able to find a dataset that meets their needs [18].

To detect personality traits through facial images, different supervised learning techniques were used, [14] proposed a new model called the personality prediction enhanced neural network (S-NNPP), which is a combination of ResNeSt architecture and a soft threshold architecture, the study of [16] proposed to use a new deep learning model called FaceNet-1, which is a combination of FaceNet architecture and a small feedback neural network.

The reviewed studies used evaluation indicators such as F1 score, average accuracy, mean square error, and coefficient of determination (R2). The survey that used average accuracy as an evaluation indicator reported the following results: [19] with 68.44%, [20] with 76%, [21] with 78%, [16] with 56.66%, [17] with 91.2% and [18] with 68%.

2) Models using other Machine Learning algorithms

Regarding the dataset used, in research on personality trait detection using other machine learning algorithms, it has also been observed that there are difficulties in obtaining facial images related to personality trait indicators, so some studies have generated their dataset from personality tests recognized by Psychology [13], [21-22], some authors had to reuse research datasets by adding some modifications [23-24] and only a few studies found datasets that meets their research needs [26],[27].

The reviewed studies used evaluation indicators such as average precision, statistical significance, root mean square error and coefficient of determination (R2). The investigations that used average precision as an evaluation indicator reported accuracies of: 87.87% [13], 77% [28], 81.66% [29], 70.11% [25] and 53.457% [27]. For the studies that used the mean square error, they obtained values of 0.4991 [22] and 0.211 [26]. Finally, other studies that used statistical significance obtained 0.24 [23] and the coefficient of determination obtained a value of less than 0.15 [24].

3) Models using statistical methods

Few studies have been conducted on personality trait detection using statistical methods because there are now other methods with better results, however, it is good to know them to learn more about the detection of personality traits, of the studies that have used as proposed statistical methods we can mention [30], where the use of Cronbach's correlations was proposed to predict 6 personality traits using facial images obtaining an r coefficient of 0.65.

In another study, [31] used Principal Component Analysis (PCA) as a statistical method, he also added an interesting feature in his data set used, in addition to the facial images he generated images of artificial faces using FaceGen Software, he also used a factorial model of 2 personality traits, as a result of his research he obtained a coefficient of determination R2 of 0.186 and found that the results when using artificial images were very different from real facial images, he

indicated that it could open a new branch of research.

III. Design and training of the Big Five personality trait detection model

A. Dataset

Among the personality trait factor models that have been studied, the Big Five personality trait model was chosen because of the large number of scientific studies that claim to have obtained excellent results in personality description, because of its recognition and use in the area of Psychology for many years, and because its high granularity allows easy extraction of personality traits.

The nature of this study required a large set of images related to their personality trait indicators corresponding to each person assessed; previous studies used data sets with a small number of items, others used a factorial model different from that of the research, and others worked with different types of data such as video, sound or thermal images.

Therefore, it was decided to build a new dataset from another one, the First Impressions dataset was used, made in the First Impressions contest organized non-profit by [1] ChaLearn (2016). Available: https://chalearnlap.cvc.uab.cat/dataset/20/description/, which is composed of 10, 000 fifteen-second YouTube video shorts linked to their personality trait indicators, these were also obtained thanks to this organization by performing personality tests with the Amazon Mechanical Turk service.

Using the set of videos four sets of facial images were extracted and generated for the training and testing of the neural networks built by the present study. The first set of 2742 facial images consist of only the extraction of these from the videos, the second set of 3085 images adds a facial retouching process which improves the brightness, contrast and sharpness of each image according to the average values detected.

The third set of 4114 images extracts the facial area these to avoid possible unnecessary background data that may decrease the accuracy of the model, and the last set of 3085 images adds the facial retouching to the third set to increase the quality of the images and thus obtain better results.

B. Detection of the big five personality traits

In this work, different models that were used for the detection of personality traits through facial images and also those of related studies were analyzed, of which excellent results have been observed in the models that used residual neural networks [14], the nature of this type of network allowed them to take advantage of large data sets and obtain high accuracy.

Currently, new neural network models have been designed that are capable of outperforming their predecessors, but they have not yet been used in studies on personality trait detection, to take advantage of this opportunity this study proposes the use of the Inception Resnet V2 residual neural network to develop the main components of the model of the present study.

Figure 1 describes the big five personality traits detection model, it is divided into 7 components, first the image pre-processing component generates 3 additional images from the input image, obtaining 4 images in total, then each one goes through a different component, the feature extraction components using an Inception Resnet V2 model predicts the big five personality traits based on their input image, the extra feature prediction component uses the Deepface library to analyze the input image and obtain features about age, gender, emotions and racial-ethnic traits, then the Feature Fusion component groups all the obtained features and prepares it for the next prediction, finally the personality trait classification component receives the features and predicts the final five big five personality traits of the model.

Each component of the model designed by this study is described below:

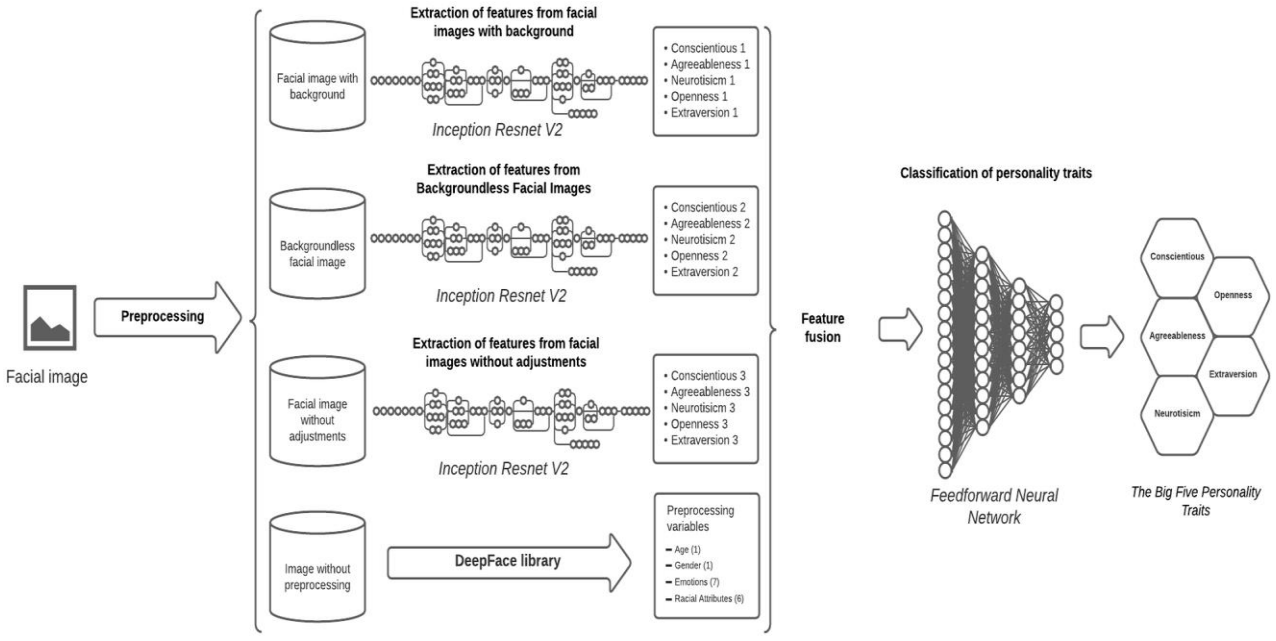

Figure 1. Big Five personality trait detection model

1) Input image preprocessing

The input image goes through a pre-processing process created by this study, the intention of performing this procedure was to omit possible variables that affect the prediction of the model, first the image is resized to 299 x 299 pixels, then the brightness is modified, contrast and sharpness of the image based on their average values and other fixed indicators proposed by the research, then a copy of the image given at the beginning is made, then the facial area is extracted from it using the DeepFace library which uses a trained model to detect the position of the pixels that represent facial areas in an image, Once the facial position is obtained, it is resized and brightness, contrast and sharpness adjustments are made, as a result of the pre-processing three images are obtained, the first is the one sent by the user, the second is the image with brightness, contrast and sharpness adjusted and the third is only the facial area also with brightness, contrast and sharpness adjusted, all images were resized to 299 x 299 pixels to be used by the neural networks trained in this model.

2) Feature extraction from facial images

This section consists of extracting the five major personality features for each of the three images generated by the pre-processing algorithms, in total 15 features are obtained, which will be sent to the feature fusion component to later serve as input for the last component of the model, for each type of image a residual neural network Inception Resnet V2 adapted for the study is trained, as a base we used the weights already trained with the ImageNet dataset given by Keras, 750 of its initial 780 layers were blocked to maintain much of the learning on facial images, additionally two layers were created, one of 1024 neurons with relu activation function and a second layer of 5 output neurons with linear activation function to refer to the five major personality traits predicted by each network.

3) Feature fusion

In this section the 15 features obtained by the trained residual neural networks are grouped and additionally using the DeepFace library on the input facial image 15 more attributes are added describing other data of the related person such as his age, gender, emotions and some of his ethnic-racial attributes obtaining 30 features in total, table 1 lists the resulting features.

Order	Description	Possible values
1	Trait Responsibility 1	From 0 to 1 (Decimal)
2	Trait Agreeableness 1	From 0 to 1 (Decimal)
3	Trait Emotional Stability 1	From 0 to 1 (Decimal)
4	Trait Openness to experience 1	From 0 to 1 (Decimal)
5	Trait Extraversion 1	From 0 to 1 (Decimal)
6	Trait Responsibility 2	From 0 to 1 (Decimal)
7	Trait Agreeableness 2	From 0 to 1 (Decimal)
8	Trait Emotional Stability 2	From 0 to 1 (Decimal)
9	Trait Openness to experience 2	From 0 to 1 (Decimal)
10	Trait Extraversion 2	From 0 to 1 (Decimal)
11	Trait Responsibility 3	From 0 to 1 (Decimal)
12	Trait Agreeableness 3	From 0 to 1 (Decimal)
13	Trait Emotional Stability 3	From 0 to 1 (Decimal)
14	Openness to experience 3	From 0 to 1 (Decimal)
15	Trait Extraversion 3	From 0 to 1 (Decimal)
16	Age Indicator	From 1 to 100 (Integer)
17	Gender Indicator	0 or 1
18	Emotion Indicator Anger	From 0 to 1 (Decimal)
19	Emotion Indicator Disgust	From 0 to 1 (Decimal)
20	Emotion Indicator Fear	From 0 to 1 (Decimal)
21	Emotion Indicator Happiness	From 0 to 1 (Decimal)
22	Emotion Indicator Sadness	From 0 to 1 (Decimal)
23	Emotion Indicator Surprise	From 0 to 1 (Decimal)
24	Emotion Indicator Neutrality	From 0 to 1 (Decimal)
25	Ethnic-Racial Indicator Asian	From 0 to 1 (Decimal)
26	Ethnic-racial Indicator Indian	From 0 to 1 (Decimal)
27	Ethnic-racial Indicator	From 0 to 1

	White	(Decimal)
28	Ethnic-racial Indicator	From 0 to 1
	Black	(Decimal)
29	Ethnic-racial Indicator	From 0 to 1
	Middle Eastern	(Decimal)
30	Ethnic-Racial Indicator	From 0 to 1
	Latino Hispanic	(Decimal)

Table I. Facial traits obtained.

4) Classification of the five main personality traits

This last section consists of predicting the final results of the model, for its development a FeedForward neural network of 4 layers was used (1 input, 2 hidden and 1 output layer), the input layer is of 30 neurons, which refer to the data obtained in the fusion of features, the hidden layers has 12 and 8 neurons respectively, each one was given a Sigmoid activation function and the output layer is of 5 neurons, each one representing a personality trait, this layer was given a Softmax activation function, figure 2 describes the structure of the neural network used.

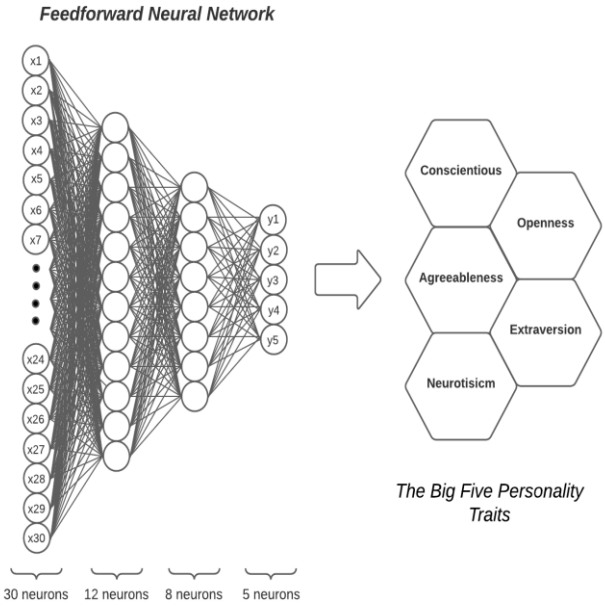

Figure 2. Feedforward Neural Network used for the final prediction of personality traits of the model.

This component returns as a result the final five major personality traits of the detection which are Extraversion, Agreeableness, Responsibility, Emotional Stability and Openness to Experience.

IV. Results

A. Division of the data set

In this study, a new dataset of 13026 images in total was built, which were divided into 4 groups with the aim of testing with various types of facial images and integrating them in such a way that better accuracy can be obtained, in turn each subset was partitioned according to its type of use, 70% of the data destined for neural network training and 30% for validation and testing, Table 2 better describes the function of each subset of data.

Model	N° Images	Division according to use
01	2742	1920 for training
	images	822 for testing
02	3085 images	2160 for training
		925 for testing
03	4114 images	2880 for training
		1234 for testing
04	3085 images	2160 for training
		925 for testing

Table II. Division of the data set.

B. Model 01: Personality trait extractor from facial images with background and retouching

This model was trained using 120 mini-batches of 16 images, and resulted in a MAPE score of 1.35, a mean square error of 2.29 and an accuracy of 53.8%. Table 3 details the results of model 3for each personality trait and Figure 3 shows the growth of the MAPE score for each mini-batch.

Model	MAPE	MSE	Accuracy
Extraversion	1.92	2.8313	0.41
Agreeableness	1.67	4.2849	0.63
Responsibility	1.39	2.4717	0.5
Emotional Stability	1.07	1.3128	0.56
Openness to experience	0.68	0.5507	0.59
Average	1.35	2.2903	0.538

Table III. Evaluation metrics for model 01.

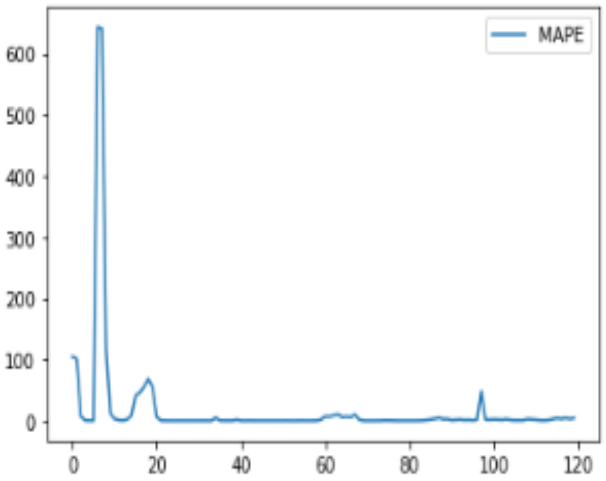

Figure 3. MAPE score for each mini training batch of model 01

C. Model 02: Personality trait extractor from facial images with background and without enhancement

This model was trained using 135 mini-batches of 16 images, and resulted in a MAPE score of 0.3286, a mean square error of 0.0406 and an accuracy of 62.4%. Table 4 details the model results for each personality trait and Figure 4 shows the growth of the MAPE score for each mini-batch.

Model	MAPE	MSE	Accuracy
Extraversion	0.3227	0.0311	0.71
Agreeableness	0.2791	0.0327	0.68
Responsibility	0.3157	0.0414	0.54
Emotional Stability	0.3486	0.0430	0.56
Openness to experience	0.3768	0.0547	0.63
Average	0.3286	0.0406	0.624

Table IV. Evaluation metrics of model 02.

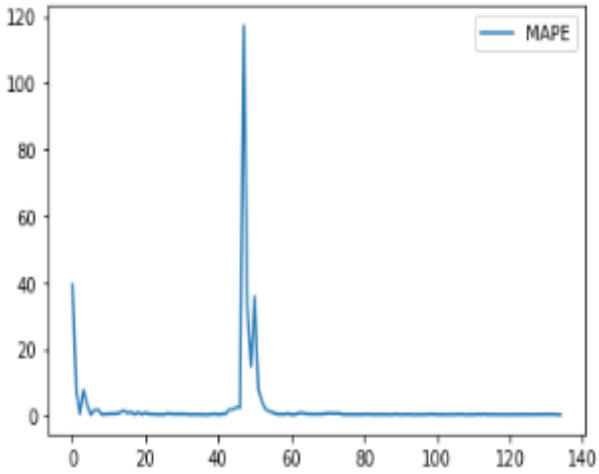

Figure 4. MAPE score for each mini-training batch in model 02

D. Model 03: Personality feature extractor from facial images without background

This model was trained using 180 mini-batches of 16 images, and resulted in a MAPE score of 0.2334, a mean square error of 0.0221 and an accuracy of 63.2%. Table 5 details the model results for each personality trait and Figure 5 shows the growth of the MAPE score for each mini-batch.

Model	MAPE	MSE	Accuracy
Extraversion	0.2620	0.0217	0.63
Agreeableness	0.1850	0.0163	0.7
Responsibility	0.2500	0.0237	0.6
Emotional Stability	0.2637	0.0253	0.61
Openness to experience	0.2160	0.0234	0.62
Average	0.2334	0.0221	0.632

Table V. Model 03 evaluation metrics.

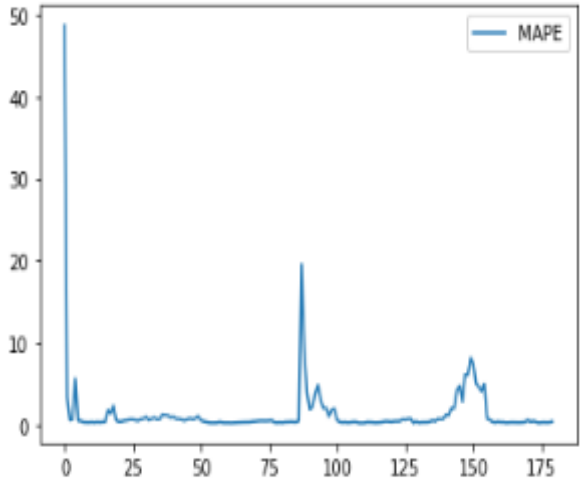

Figure 5. MAPE score for each mini training batch of model 03

E. Model 04: Predictor of personality traits

This model was trained using 135 mini-batches of 16 images, and resulted in a MAPE score of -0.15, a mean square error of 0.0254 and a mean absolute error of 0.1292. Table 6 details the model results for each personality trait and Figure 6 shows the growth of the R2 score for each mini-batch.

Model	R2	MSE	Accuracy
Extraversion	0.2577	0.0211	0.64
Agreeableness	0.1820	0.0147	0.72
Responsibility	0.2334	0.0215	0.61
Emotional Stability	0.2625	0.0250	0.63
Openness to experience	0.2056	0.0222	0.62
Average	0.2282	0.0209	0.6440

Table VI. Evaluation metrics of model 04.

Analyzing the obtained results, we can observe that the training with images without background has obtained a better accuracy than the other models, we can also mention that using an extra neural network in model 4 improved a little the results and allowed to predict the personality traits in the case in which the model the DeepFace library did not recognize the facial area of the image, in the next section we discuss in more detail the obtained results.

F. Discussion

This work serves as evidence that it is possible to predict the Big Five personality traits using non-static, low-quality facial images. Applying pre-processing techniques before prediction avoided image noise problems and allowed the model to adapt to varied images, furthermore the large number of images used in the training phase allowed to

take advantage of the structure of a residual neural network with a large size of neurons. This finding is considered as a great contribution in personality trait detection since most related studies have trained their models with limited facial images (static [14], [[32]-[20]], [[32]-[20]], high quality [14] or profile-only [26]) and another advantage to note is that the Inception Resnet V2 neural network, considered a superior neural network to the ResNeSt50 [14], ResNet73 [32], VGG16 [20], convolutions [15], [18] and FeedForward [19] networks used in previous studies, has been used as a basis.

The results exceeded the accuracy of 56.66% of the study [16], obtaining an accuracy of 64.40% to predict the five major personality traits through a facial image, we consider that the results were obtained by testing with new neural networks designed to overcome the barriers of their predecessors, also the present study used images with low quality, this being a limit for [14] and other previous studies.

This study used the strategy described in the work of [17] to improve the model prediction results, which consisted of extracting the facial area of the images to only consider facial features and not the environment or background is shown, however, this study added some extra features such as emotion and ethnic-racial features to improve the accuracy of the model.

V. Conclusion and future work

The present study proposed a new model to detect the five major personality traits of a person using a facial image of him/her, the model obtained an accuracy of 64% with which it can be used by other studies interested in affective computing, we can mention the factors that contributed the most in these results, the type of residual neural network Inception Resnet V2 allowed the model to take advantage of the number of images, having the model previously trained to identify facial images allowed the model training stages to be accelerated and to focus more on the identification of the five major personality traits, finally using facial images without background and some variables on emotions, age, gender and ethnic-racial traits obtained thanks to the DeepFace library, allowed better results in the final model because personality is related to these.

It is proposed to those interested in the automatic detection of personality traits to continue developing studies on this topic in the future, since many services are currently appearing that will need to know more about personality to provide a better quality to their users, it is invited to use other factorial models such as Eysenck's PEN model and to test with larger datasets than the one presented in this study.

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