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First Results on Using Transformer Architecture for Extroversion Personality Trait Recognition

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ABSTRACT

Personality traits are characteristics that can describe a person's behavior, also reflecting their thoughts and feelings. There are those who support the idea that traits can be strong predictors of leadership, implying emotional stability of the individual. Knowing the importance of the subject, areas such as psychology and neuropsychology have been studying and analyzing personality, aiming to better understand such patterns that guide behavior. A model widely accepted to categorize personality traits is known as *Big Five* and uses the acronym OCEAN: Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism. On the other hand, new approaches that emerged from the field of computer vision allow to analyzing personality from visual data, making this new area of research quite attractive for researchers. This work presents an initial study of the use of the Transformer architecture to analyze personality traits, with a specific focus on extroversion, using digital videos of human faces. A literature review was carried out focusing on the application of computational techniques in this issue involving deep learning and Transformers. We also accomplished an experiment analysing Extroversion personality trait, as a starting point for our studies, using the ChaLearn dataset. An AUC (Area under the ROC Curve) value of 71.04% was obtained, with fine adjustment of parameters in the transformer, demonstrating the robustness of the proposed architecture.

Keywords

Personality trait Recognition, OCEAN model, Affect Computing, Video Processing.

1 INTRODUCTION

To understand what Personality Traits are, we first need to understand what are the dimensions that define them. The theory of personality traits is an approach based on the definition and evaluation, and it is related to habitual patterns of behavior, thoughts and emotions that are relatively stable over time [costa1998trait]. They are important for psychology because they help to describe and explain how people behave and react to different situations [thoresen2004big]. They also provide a structure to understand the consistency and stability of an individual's psychological characteristics in different contexts [chioqueta2005personality]. To understand human personality, theorists and psychologists have developed frameworks for organizing this vast amount of information, often using personality scales. Different feature models have been proposed in order to represent personality traits such as 16PF [cattell1986number], Big-Two [abele2007agency], HEXACO [ashton2007empirical], NEO-PI-R and NEO-FFI [sharpe2001revised]. Nevertheless, in 1961, Tupes and Christal [tupes1992recurrent] found five recurring factors in analysis of personality classifications. This model became known as the Five Great Traits, or simply *Big Five*, represented by OCEAN Acronym: Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism. The Big Five became the most adopted and influential model in the field of psychology. Among the various application areas of using a personality trait representation model, we have: **Psychology:** used to better understand human behavior and help in the diagnosis and treatment of mental disorders; **Human Resources:** evaluation of job candidates, helping in the selection of those who best fit the needs of the company; **Marketing:** Identifying consumer profile and personalizing of strategies, and **Artificial Intelligence Systems:** Considered one of the most promising areas of the moment, helping to improve the interaction between humans and machines.

Currently, the assessment of personality traits is performed mainly through questionnaires and structured interviews conducted by psychologists or other mental health professionals. Psychological studies have shown that the face can also play a central role in everyday interpersonal assessments, being of great importance for the identification of personality traits [todorov2008understanding]. Several papers have established a correlation between facial appearance and personality traits [kramer2010internal] [penton2006personality] [little2007using] [sutherland2015personality] [junior2019first] [gucluturk2017visualizing]. In this context, computer vision techniques can play an important role in supporting the assessment of personality traits.

In recent years, advances in the area of natural language processing and, in particular, the use of Transformer architecture achieved high effectiveness in textual analysis tasks. The most popular Transformer architectures include Bidirectional Encoder representations of transformers BERT [devlin2018bert] and Generative Pretrained Transformer (GPT) v1-3 [radford2018improving] [radford2019language], for instance. These models have the ability to understand and process large volumes of text, identifying complex semantic patterns and relationships. For this reason, many researchers directed their efforts to the application of this new approach in their computer vision problems, in order to obtain the first impressions about an individual's personality trait.

Transformer is based on two components, where the first encodes a source sentence x and the second decodes a target sentence y. The Encoder-Decoder structure is used in most neural sequence transduction models. The Transformer architecture proposed by Vaswani [vaswani2017attention], is an innovative approach to sequence processing, which overcame many limitations of previous approaches in Natural Language Processing (NLP). Its ability to model long-range relationships and complex contexts revolutionized the field and led to the development of powerful models such as BERT, GPT and others that achieved exceptional results. Multi-head attention is the backbone of the Transformer architecture.

This paper presents an initial study of the application of Transformers Architecture to identify extroversion personality trait through face analysis in digital videos. We intend to answer the following research question: Do Transformers offer significant benefits in the context of identifying personality traits due to their contextual learning capability, long-term representation, generalization, and interpretability? We also describe and present a systematic review of the literature in the area, summarizing gaps and opportunities, citing existing datasets and the approaches used to treat the problem of identifying personality traits. The rest of this paper is organized as follows: Section 2 presents a brief review of related works and the systematic review carried out. The approach adopted is presented in Section 3. Section 4 shows initial results and presents the performance evaluation by means of accuracy metric. Finally, in Section 5, we present the main conclusions and future work.

2 RELATED WORKS

We obtained the state-of-the-art through a systematic review of the literature (SRL) and were used these key-words: personality traits, computational Techniques, computer vision, images, videos, machine learning and deep learning, following the procedures established in the methodology proposed by [kitchenham2009systematic]. The initial survey of this systematic review resulted in 281 papers, of which 219 works analyzed were identified as not being duplicated, from these, 39 were selected. However, to cover the most recent work, an update to the SRL was carried out in May 2024, resulting in an increase of 17 new articles, bringing the total to 56. The papers were collected from 7 different databases, as can be seen in Table 1. We can see that most of the papers were selected from the IEEE database.

The analysis step of each of the selected articles was guided by three research questions:

- What computational approaches and data modalities were used to assess personality traits?
- What classification or regression models were used?
- Which dataset was used for Training and Testing?

Searched databases	Number of Papers
Web of Science	7
Science Direct	5
Springer	3
Engineering Village	3
IEEE	23
ACM	4
Scopus	10
Willey	1
Total	56

Table 1: Number of articles extracted per search base.

The SRL was carried out at the end of 2022 and updated in May 2024, thus considering works published between 2017 and 2024. Figure 1 shows the distribution of these articles over the years researched.

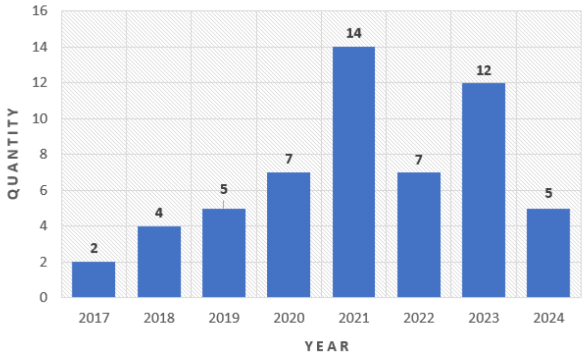

Figure 1: Papers published per year. Source: Author.

Table 2 shows some of the most relevant papers that are related to our work. In addition to highlighting the adopted approach, it also shows the modalities concerning the type of data used to assess personality traits.

Paper	Year	Approach	Modalities
Zhang et al.	2017	CNN	I
Rai, Nishant.	2016	CNN	A+I
Wei et al.	2017	CNN	A+I
Agastya et al.	2019	CNN	V+I
Yesu et al.	2021	CNN	V+I
Moreno et al.	2020	DCNN	I
Xu et al.	2021	DNN	I
Ventura et al.	2017	DAN	I
Ibrahim et al.	2023	CNN	I
Gucluturk et al.	2017	Resnet	V+I
Bounab et al.	2024	LSTM	V

Table 2: Main Features Paper | A-Audio, I-Image, V-Video

Within the established period of the SRL, we noticed a large presence in the approach to the modalities of Images and Videos. Both Ventura [Ventura2017CVPRWorkshops] and Gucluturk [gucluturk2017visualizing] in 2017 used the Regression technique for their works. While Ventura's work used the interpretability of the video modality and worked with the architecture called DAN+, which is an extension of the Descriptor Aggregation Networks (DAN), Gucluturk's model [gucluturk2017visualizing] used a ResNet Deep learning methodology, which took advantage of the visual and auditory information available in the dataset. Still in 2017, Zhang [zhang2017physiognomy] published a paper that aimed to evaluate the personality traits and intelligence of individuals from their faces, using images. They explained that the face can play a crucial role in interpersonal relationships, thus being able to impact important social events, such as elections and court decisions. The authors study uses Convolutional Neural Networks (CNN) to recognize personality traits. The work presented by Rai Nishant in 2017[rai2016bi] used Regression Assignments and CNN. Their approach aimed to predict features by combining several models including Deep Neural Networks that focused on leveraging visual information on faces. In addition to observing face information through images, this work also combine the use of audio in order to provide a more precise accuracy. In 2019, Agastya[agastya2019systematic] presented a significative systematic review of the literature, analyzing 25 papers. This work sought to understand the approaches in the recognition of personality traits using deep learning algorithms. Yesu's work in 2021[yesu2021big] has focused on image observation using Convolutional Neural Networks. His work aimed to explore the possibility of mapping the Big Five personality traits, generating a score for each of the personalities. The goal is training computers to understand the personality traits of human beings based on their facial shapes.

At the end of reading the works, we identified the lack of datasets with videos labeled with personality traits to be used in the assessments. Another point is that several Deep Learning techniques such as CNN, SVM, DAN, DNN, etc are being used, however, no work using the transformers architecture was found. This was the main motivation for pursuiving this work. The Figure 2 illustrates the distribution of the most used datasets in the articles, reflecting the papers that were selected during the SLR.

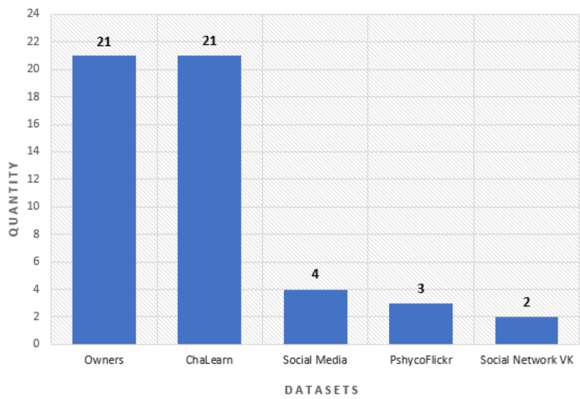

Figure 2: Dataset used by Papers selected during the SLR. Source: Author.

3 PROPOSED APPROACH

In this section we present our proposed approach to classify the extroversion personality trait. It consists of three main steps: Dataset preparation, Pre-processing and Classification, according to the pipeline shown in Figure 3. Each step is described through the remainder of this section.

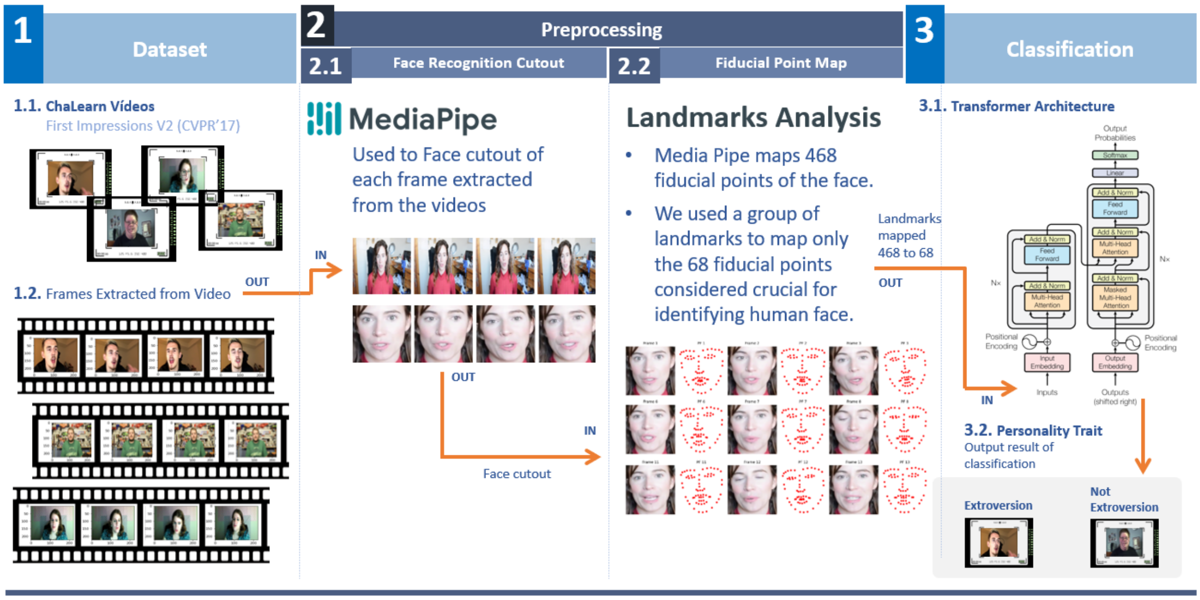

Figure 3: Proposed Methodology approach using Transformer for extroversion personality trait recognition. Source: Author

3.1 Dataset preparation

This step is responsible for presenting dataset characteristics and how its preparation was implemented.

3.1.1 First Impressions dataset

First Impressions is a personality trait dataset comprising 10,000 clips (average length 15 seconds) extracted from over 3,000 different high definition (HD) YouTube videos of people looking and speaking in English into a camera. Videos are split into training, validation, and testing sets with an aspect ratio of 3:1:1. People in the video have different gender, age, nationality and ethnicity[escalante2020modeling]. Videos were labeled using Amazon MechanicalTurk (AMT) service; Its post processing generate the values for the different personality traits. Some principles were adopted to guarantee the reliability of the labels[escalante2020modeling]. The personality traits considered were those of the Big Five model.

3.1.2 Frame Extraction

In this step we extracted the ChaLearn dataset package *First Impressions V2 (CVPR'17)* [1]. Also, we selected frames taken from the videos at regular intervals. For our analyses, we developed a Frame extractor from the labeled videos of the ChaLearn dataset and we set the Number of Frames as 8 and the frame format as *(224, 224, 3)*. Figure 4 illustrates a frame extraction for the **"zEyRyTnIw5I.005.mp4"** video, classified as Extroverted.

[1] https://chalearnlap.cvc.uab.cat/

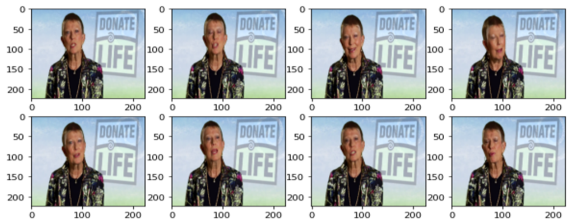

Figure 4: Resulting frames obtained from video extraction step. Source: Author.

3.2 Preprocessing

This step consists of two data preparation tasks for the classification model: Face Recognition CutOut, and Fiducial Point Map. In our proposed work, **Face Recognition CutOut** from video frames is performed by Google Media Pipe Face Mesh Library. Google MediaPipe is able to predict and return landmarks of a human face based on only one perspective with high accuracy [ali2021classical]. Human face identification through facial alignment is one of the main challenges of the pre-processing stage in the general facial recognition process. So, Google's MediaPipe library uses a deep learning model trained on a large amount of data to perform facial mapping using landmarks. Specifically, MediaPipe Face Detection and MediaPipe Face Mesh are two CNN models used to detect faces and estimate facial landmarks, respectively. In the second preprocessing task, to perform the **Fiducial Point Map**, we defined a list with just 68 landmarks that contains the indices of the facial landmarks that will be extracted from the detected face [zhang2022applications]. These indices correspond to the fiducial points identified by MediaPipe's Face Mesh model. The Face Mesh model is capable of detecting up to 468 facial landmarks in an image. Thus, only 68 of the 468 points are selected for extraction. These points were chosen because they are the most relevant points for face recognition analysis. This list of fiducial points is essential for extracting relevant facial features from an image, such as the contours of the face, the position of the eyes, mouth, etc [samaan2022mediapipe]. These features can be used for a variety of purposes, such as facial recognition, facial expression analysis, blink detection, among other computer vision applications.

3.3 Classification

The classification of personality traits is performed using the Transformers architecture. The Transformers architecture was proposed by Vaswani and his team, in the article Attention is All You Need[vaswani2017attention], and it is the approach of a new simple network architecture, based only on attention mechanisms, not requiring recurrence and convolutions. Attention mechanisms in neural networks, such as Transformer, allow the network to focus on specific parts of the input during processing. Instead of treating all input at once, these mechanisms prioritize certain parts, giving them more "attention" during calculation. Thus, in the context of images or videos, attention mechanisms allow the network to focus on specific regions of the image or specific frames of the video. Instead of processing the image as a whole at once, the network with attention mechanisms can direct its attention to specific parts of the image that are most relevant to the task at hand. This allows for a more focused and adaptive approach to processing visual information, which can lead to better performance in tasks such as object recognition, image segmentation or video analysis. This third block is divided into two stages. The first one, is the **Transformer Model:** Step where we will apply the Transformer architecture in Image Classification to identify personality traits and the second, is the **Personality Traits Classification:** Results of image classification, according to their respective personality traits.

4 INITIAL EXPERIMENT & RESULTS

In this section we show our initial results obtained for the extroversion personality trait through the proposed approach described in the previous section. Table 3 shows the Hyperparameters that were used in this first experiment.

- N HEADS (Number of Heads): This parameter refers to the number of attention heads in a Transformer model.
- N LAYERS (Number of layers): Indicates the number of layers stacked in the Transformer model.

Hyper Parameter	Value
N_HEADS	2
N_LAYERS	5
DROPOUT	0.3
MLP	256
BATCH SIZE	1280
ACTIVATION	gelu
D_MODEL	128
D_FF	512
EPOCHS	5000

Table 3: Main Feature parameters

- DROPOUT: Dropout is a regularization technique commonly used in neural networks to prevent overfitting. This value represents the dropout rate, that is, the proportion of units that will be temporarily deactivated randomly during training to prevent the network from becoming too dependent on certain neurons.
- MLP (Multilayer Perceptron): This is the size of the hidden layer of the feedforward neural network inside the Transformer.
- BATCH SIZE: The batch size indicates the number of training examples used in one iteration.
- ACTIVATION: Refers to the activation function used in the hidden layers of the neural network.
- D MODEL (Model dimension): It is the dimension of representation of the input and output vectors in each layer of the model.
- D FF (Feedforward Dimension): It is the dimension of the hidden layer in the feedforward neural network inside the Transformer.
- EPOCHS (Epochs): Represents the number of times the entire dataset is passed through the model during training.

We employ the TensorFlow framework to train the proposed network on a server with 64-GB RAM, Xeon 12x 2.4GHz (computer equipped with a Xeon processor with 12 processing cores), and 1x TITAN X (computer capable of handling advanced graphics and computationally intensive tasks). Each video in First Impressions Dataset receives a score associated with each of the personality traits: extroversion, neuroticism, agreeableness, conscientiousness and openness. In this way, and taking into account the 6000 videos destined for the training stage, we create a new dataset designed for a binary classification, in which these videos were separated into two distinct classes: Extroversion and non-Extroversion. In our case, we used a threshold of 0.5 for the extroversion attribute, as recommended by [escalante2020modeling].

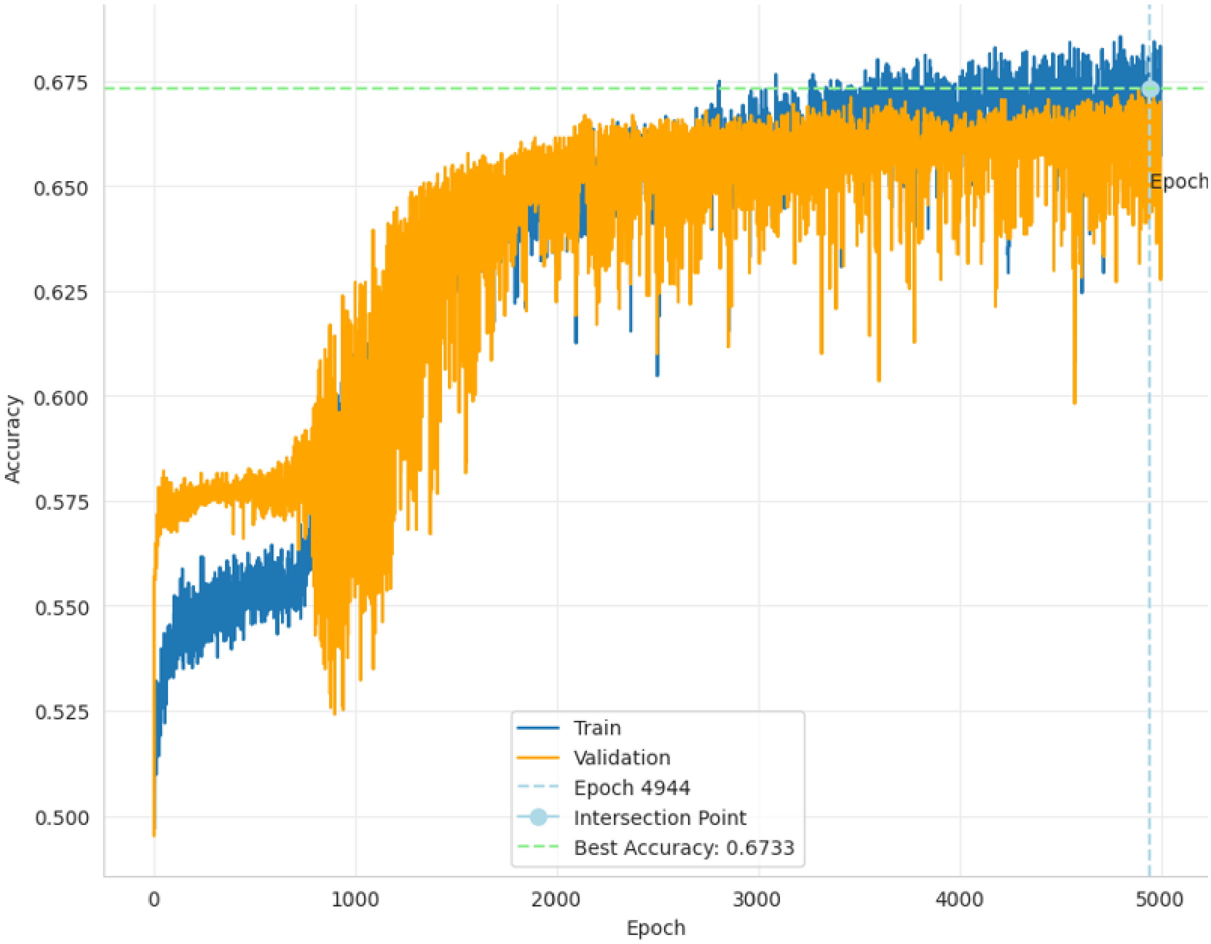

Figure 5: Accuracy obtained in the proposed approach. Source: Author.

Table 4 shows the number of videos per class in this initial experiment.

Personality Trait	Quantity	%
Extraversion	2.688	44.8
Non-Extraversion	3.312	55.2
Total	6.000	100.0

Table 4: Number of Videos for Extraversion class

Finally, following the training stage, we implemented the classification stage for a total of 2000 videos from the validation set. Figure 5 presents the Accuracy metric obtained from the both training and validation sets according to the number of epochs. We observe that the training convergence in 750 epochs demonstrates that the model is learning the patterns in the training data, from this moment on. This is positive, as it implies that the model can generalize and adjust its weights to achieve stable performance for unknown data. A validation AUC accuracy of 71,04% is very positive, demonstrating satisfactory performance, indicating that the model is generalizing well to data not seen during training. It is also possible to verify that validation accuracy followed training accuracy. When this happens in a machine learning model, it is generally a positive sign as it suggests that the model is generalizing well, which is one of the main goals in model training.

Table 5 shows a comparison of the AUC accuracy results for related works, exclusively to the Extroversion personality trait, comparing to the accuracy obtained in the first experiment carried out in our proposed approach.

Paper	Approach	AUC
Proposed Approach	Transformer	71.04%
NJU-LAMDA	CNN	83.91%
Evolgen	LSTM	82.50%
DCC	ResNet	81.78%
Ucas	CNN	84.21%
BU-KNU	CNN	84.38%
Pandora	CNN	80.97%
Pilab	CNN+DAN	71.39%
Kaizoku	CNN	72.86%
ITU-SiMiT	CNN	44.10%

Table 5: Performance comparison: AUC results for the Extroversion personality Trait [ponce2016chalearn]

5 CONCLUSIONS

This work carried out extroversion personality trait classification using a Transformer architecture. A dataset widely adopted in the literature was used in the experiments, obtaining an initial AUC of 71,04%, with few adjustments in the hyperparameters of the classification model. For now, the goal was to validate the proposed pipeline. In a scenario of binary classification of personality traits, extroversion or not, Transformers emerge as a powerful and innovative tool. Its ability to capture complex contexts, learn meaningful representations and deal with image sequences opens opportunities to a deeper understanding of the relationship between video and personality. Therefore, in this context, the **main contributions** of our paper was providing a systematic literature review of the use of computational techniques in order to classify personality traits. In addition, we present a pipeline in a novel approach able to classify personality traits. As future works, the challenges we hope to face are related to three tasks: **1. Descriptors -** Use of new descriptors that combine facial landmarks; **2. Personality Traits -** Obtain satisfactory accuracy results involving the five great personality traits that make up the Big Five model; and, **3. Data Analysis -** Analyze distinct datasets, allowing personality traits to be identified on a large scale.

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