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Article

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Personality prediction from Five-Factor Facial Traits using Deep learning

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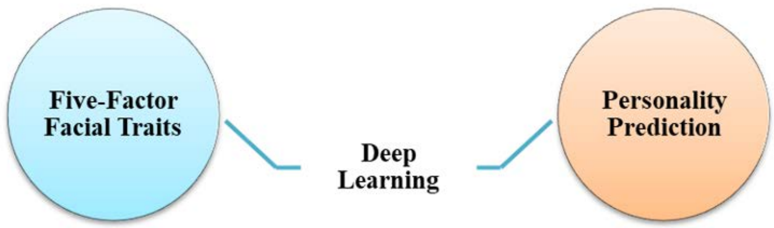
ABSTRACT

In this paper, a fine-tuned deep learning model is presented for the prediction of personality using facial images. It can measure personality qualities from a portrait photograph using the Five-Factor model (Big Five). To assess the efficacy of this method, a fresh corpus of 30,935 portraits with their associated personality characteristic was retrieved from an existing video resource (First Impressions, ChaLearn) and labeled with redundant pairwise comparisons to assure consistency. For each Big Five feature, the provided model will categorize these qualities into a binary class: openness to experience (O), conscientiousness (C), extraversion (E), agreeableness (A), and neuroticism (N). The experiment was conducted on three baseline models and achieved an average accuracy of 81% which shows an improvement of 3% over existing state-of-art models.



Keywords: Personality Prediction, Facial Images, Five-Factor model, Fine-tuned Learning

INTRODUCTION

Despite the rapid development of Human-Computer Interaction (HCI) and unrelenting efforts to enhance the user experience with computer systems, it is now commonly accepted that agents must be able to detect and respond to users' affective states. Although an essential part of human behavior, affect is a highly subjective phenomenon that is influenced by a variety of environmental and psychological factors, such as personality.[1] Users of social media have the chance to create an online persona by sharing content (such as writing, images, or links) or by interacting with other users. Users' self-presentation is a sort of behavior that is typically influenced by variations in demographic or psychological characteristics.[2] Facial expressions (FE) are essential affect signaling systems that provide indications about a person's emotional state.[3] They make up the core of human communication in social circumstances, together with voice, language, hands, and body posture. Behavioral science, neuroscience, and artificial intelligence all intersect in the field of automatic FE recognition (AFER). One of the most crucial nonverbal cues that HMI systems use to identify internal human emotions is facial expression, which is crucial for social interaction.[4]

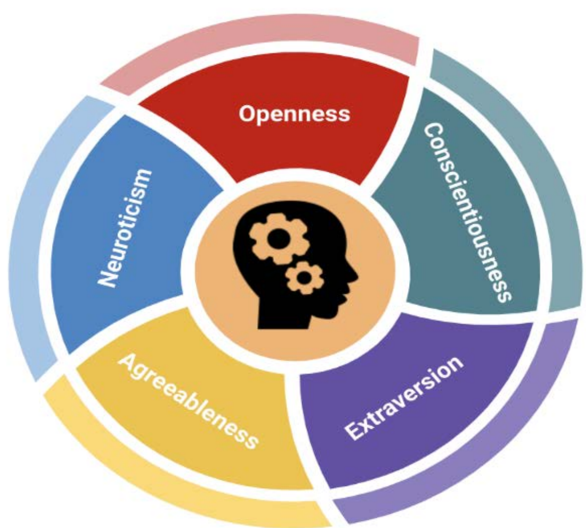


Figure 1. Personality Traits

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We now use biometric technology daily as its popularity is growing quickly. A biometric system's objective is to automatically identify people based on their biological and/or behavioral traits.[5-10] The degree of human supervision should be kept to a minimum due to the nature of automatic processing and the capture process, and system components should allow for the unsupervised acquisition of biometric data.[11-15] Due to its broad application in international border control, face biometrics play a significant role among the biometric systems that are deployed in an operational setting. Both prepared and spontaneous facial expressions have been used in facial expression recognition (FER) studies under a variety of imaging circumstances, such as different head postures, lighting settings, resolutions, and occlusion.[16,17]

The geometry-based techniques leverage the size and the relative position of significant facial components to extract facial traits. First, the orientation and the edges of significant face components are identified. The discovered edges and directions are then used to create feature vectors.[18] For this, gradient analysis and the Canny filter are frequently employed. Applying Local Binary Patterns (LBP) prevents lighting effects. To produce a feature vector for the facial image, LBP creates a histogram, as presented in Figure 2.

Since studying video also involves examining frames (pictures) and audio data, personality detection from video data is related to personality extraction from image and audio data.[19] Based on the shape of the face, it is possible to determine a person's basic personality.[20,21]

The eyebrow, lip, nose, and eyes were used as feature extraction on a portion of the face. How to extract information from the four parts of the face is unclear in this study's formulation of feature extraction. The physical characteristics of the face as seen in ambient face images can play a significant role in simulating the dimensions of the trait factors that underlie social qualities. Accurate conclusions about personality traits can be drawn from the features. This is reinforced by studies that measure intellect and personality traits from morphological elements of the face, forecast the personality impressions for a specific facial-depiction movie, and determine personality qualities from a face image.[22-26]

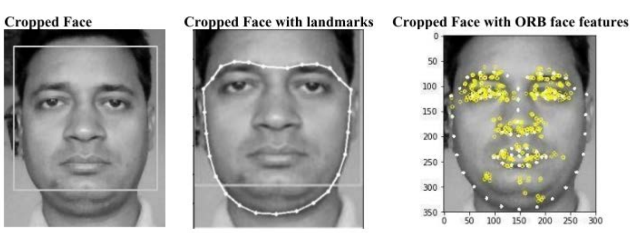


Figure 2. Detection of Facial Features for Mapping.[8]

RELATED WORK

To predict the Sixteen Personality Factors from face cues using the Facial Action Coding System, a novel three-layered neural network-based architecture is suggested by Gavrilescu & Vizireanu.[11] The suggested architecture accurately foretells warmth, emotional stability, liveliness, social boldness, sensitivity, vigilance, and tension with a rate of over 80%. Additionally, we demonstrate a significant correlation between the emotions generated by the study subjects and the high degree of predictability for each of the 16 personality traits. Three different approaches—ANN, SVM, and deep learning - are used to identify the personality qualities from a facial image. A color segmentation method that identifies the face region of an image was proposed by Ilmini.[12] After that, the personality recognition process uses the retrieved image as input. Manually selected facial features are entered into ANN and SVM. Xu et al.[13] assessed the potential link between static face contour images and personality features to achieve the goal of a comprehensive comprehension of a person's personality attributes. According to the experimental findings, 2.5D static face contour images may accurately identify people's multidimensional personality traits more accurately than 2D images when employing a deep neural network that has been trained using huge labeled datasets. Using a cascade of artificial neural networks (ANNs) trained to predict personality traits from static face images, the relationships of facial picture cues with self-reported Kachur et al.[14] examined Big Five personality traits. The main assumption is that machine learning can be used to extract personality indicators from a real-life image graph. To fix two significant problems that typically arise in automatic personality analysis systems currently in use: attempting to deduce personality qualities from very brief video segments or even single frames as opposed to long-term behavior; There are no techniques for encoding individual facial dynamics for personality recognition. To address these problems, Song et al.[15] provided a unique Rank Loss that employs the temporal evolution of facial movements naturally occurring rather than personality labels for self-supervised learning of facial dynamics. Biel & Gatica-perez[17] proposed the application of cutting-edge facial expression recognition technology to identify users of conversational vlogs. First, suggest using a variety of activity cues to categorize vloggers using frame-by-frame estimates of the emotional expressions on their faces. The task of automatically predicting vloggers' personalities based on facial expressions and the Big-Five qualities was then presented, with the outcomes. A novel framework for identifying personality traits based on users' physiological reactions to emotive movie snippets is presented by Wache et al.[18] Analysis of responses to emotionally homogenous (i.e., high valence, high arousal) video reveals personality variations more clearly, and significantly above-chance recognition is attained for all five traits. A methodology for resolving the issue of predicting a user's personality attributes from films was put forth by Suman et al.[19] From the user's video, ambient, face, and audio elements are retrieved. For the prediction of the ultimate output, these features are utilized. A methodology for resolving the issue of predicting a user's personality qualities from films was put out by Qin et al.[20] The user's video is used to extract ambient, face, and audio elements. The predicted ultimate output is based on these features. Building a revolutionary non-invasive approach to identify the Big-Five personality traits based on facial features obtained using the Facial Action Coding System is the goal of Gavrilescu.[21] The findings indicate a relationship between a person's personality qualities and the FACS action units present in face features at their highest intensities.

METHODOLOGY USED

Facial feature extraction using deep learning involves analyzing facial images to capture patterns and structures. This can be used to identify personality traits based on facial features. The assumption is that certain facial attributes may be associated with specific personality characteristics. These features include shape, texture, and spatial distribution of facial attributes. In the proposed model, the learning algorithms can be trained on labeled facial images and personality trait annotations to predict or classify personality traits. By learning patterns from the data, the algorithm creates a model that maps facial features to specific personality traits. The entire methodology is divided in three steps: Pre-processing, facial feature extraction, and personality trait prediction. The sequential representation of this work is shown Figure 3.

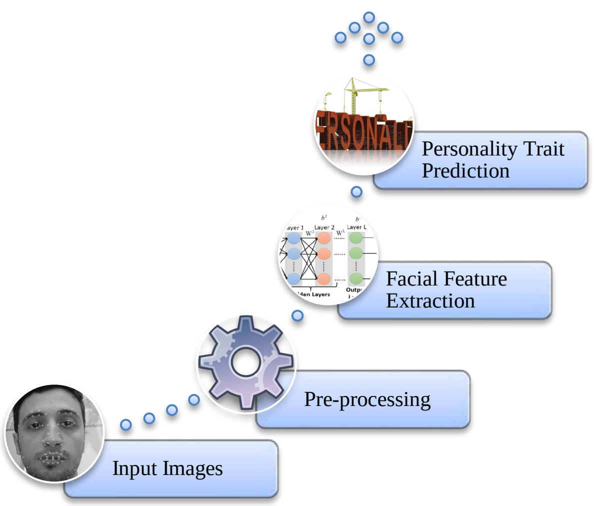


Figure 3. Working flow of current Model

1.1 Pre-processing

It has been determined that the facial image will serve as the input image. The first thing that is done is the pre-processing step, which involves identifying the borders, cropping the borders, applying the transformation to straighten the page, applying the sharpening kernel, identifying and cropping the borders, and eliminating noise, correcting skew and size. To get the initial input image ready for further processing, it must first be scanned and examined. Using a Gaussian filter that has an Otsu threshold, the noise is eliminated after it has been determined where the page boundary is located. After that, a greyscale image is created from the original image.

1.2 Facial Feature Extraction

A convolutional neural network, also known as a CNN, is an architecture-specific multi-layered neural network. It is used to recognize intricate details in data. The following diagram, Figure 4, illustrates the basic CNN architecture. It is possible to use it to classify the subject matter of a variety of images. The model can consider the images as input. ANN is influenced by the workings of the human brain in a manner that is comparable to CNN. CNNs can classify images by extracting features from them, very similar to how the human brain looks for features to identify the items it encounters. The CNN contains both convolutional layers and Maxpooling layers in its network structure. A connection has been made between the completely connected layer and the nth pooling layer. During the learning phase, it incorporates a few backpropagation steps to minimize the amount of information that is lost. In the end, it will generate the output by making use of an activation function such as Softmax, random forest, or support vector machine. In this article, we offer fine-tuned models such as ResNet50 and assess their overall performance (Figure 5).

The major motivation behind ResNet50, a deep residual neural network learning approach, was the degradation problem as well as the incapacity of several non-linear layers to comprehend identity mappings (ResNet). For ResNet to function properly, a significant number of layered residual units are required. When the network was created, these residual units were used as the basic components or foundation components of the network. The ResNet framework, which is made up of a collection of residual units, is constructed using these foundation components as its building blocks. Convolution layers, pooling layers (a new layer introduced after the convolutional layer), and layer components combine to form the residual units. Pooling layers are the new layer introduced after the convolutional layer. Even though it utilizes 3x3 filters, ResNet has a depth that is almost eight times that of the VGG network. In place of fully-connected layers, global average pooling layers are utilized, which is another factor that contributes to the problem. In the end, a customized classification layer intended for personality detection was developed. Transfer learning is similar to the concept of honing one's skills. A method of machine learning known as transfer learning employs the information learned from process training on one sort of problem to train on another kind of task or area that is comparable. Initial layers of a DL model are often trained to recognize task-specific properties. Fine-tuning involves replacing some of the final layers of trained networks that have been obtained through transfer learning. After this, the network is

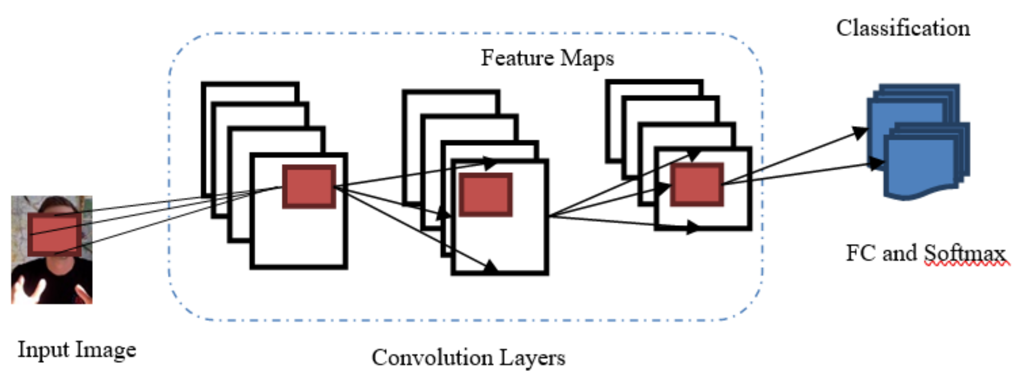


Figure 4. Basic CNN Architecture

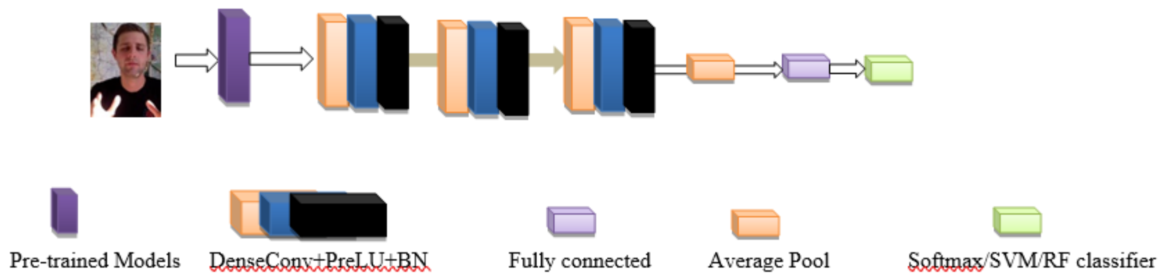


Figure 5. Fine-Tuned Model Architecture

retrained for the desired target. Even though there is still some schooling involved, the time spent on fine-tuned learning trials is substantially less than what would be spent beginning from scratch. In addition, as compared to models that were developed wholly from scratch, these have a better degree of accuracy. Batch normalization is typically combined with a fine-tuned model to mitigate the problems that are brought on by an internal covariate shift. During the training of deep neural networks (DNN) in addition to artificial neural networks (ANN), the output of one layer is used as the input for the layer that comes after it. The propagation of the inputs to the layer changes substantially as a result of the values from earlier layers being subject to change over time while the network is being trained. Batch normalization makes it possible to use significantly higher learning rates, lessens the initiation concern, and, in certain circumstances, eliminates the need for dropouts to be performed. Batch normalization might be useful in two different ways: first, it might make learning more efficient; second, it might make accuracy better in general. Throughout the entirety of the research, batch normalization was utilized, in addition to the application of the hybrid loss function and parametric Rectified Linear Units (ReLU) activation function. This particular loss function was developed to address the issue of class imbalance. The loss function is explained in the following way:

$$\boldsymbol{Loss_H = \frac{1}{N}\sum_{i=1}^{I}\sum_{j=1}^{J} FC_{ij}} \quad (5)$$

Where, I = Number of layers in the model, FC_{ij} = Focal loss, and J = Number of loss functions.

For the fine-tuned model, the parametric ReLU algorithm is used since it allows for the adjustment of the learning parameters based on the learning rate and does not suffer from the vanishing gradient problem.

Result Analysis

Dataset Used: As mentioned before, in this paper, the Five-Factor model (Big Five) is adopted for model training. This dataset is collected from open source.[27] A sample of some images is presented in Figure 6.

Further, the results of fine-tuned models are assessed using the accuracy, precision, recall, and f1_score measure as shown in Table 1. To determine whether the model will be able to converge with so few iterations and which suffered from the degrading issue, every experimentation was run for a total of 100 epochs. All fine-tuned networks are hyper-parameterized. The batch size of 64 for the network's training was used. In this study, a comparative state of art deep learning model is presented for fine-tuned deep learning models. Accuracy. Precision, recall, and f1_score are used for the performance evaluation.

Figure 6. Dataset Sample[27]

Mathematically, they are represented as:

$$\boldsymbol{Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + F}} \quad (i)$$

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \quad (ii)$$

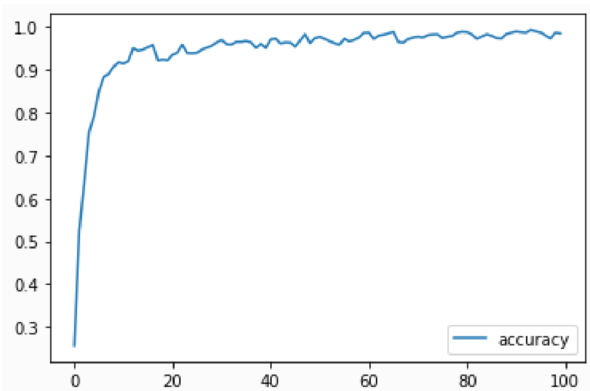
$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \quad (iii)$$

$$F1\_score = \frac{2}{1/precision + 1/Recall} \quad (iv)$$

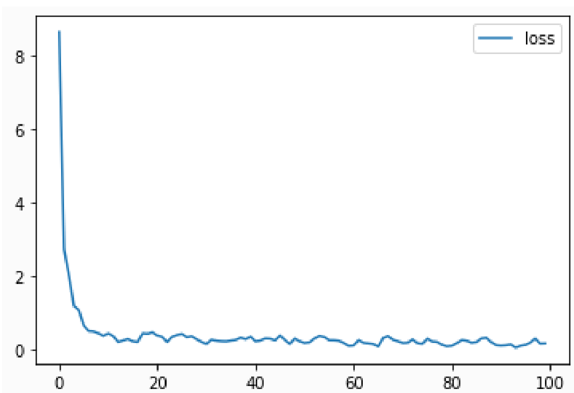
Where True Positive, True Negative, False Positive, and False Negative are true positive, true negative, false positive and false negative instances respectively. Below in Fig 7, the paper presented the training accuracy and loss graph of fine-tuned ResNet50 model. This model has shown a training accuracy of approx. 97% and training loss of approx. 0.1. This shows better training with minimum loss.

Table 1. Performance Comparison

Model	Accuracy	Precision	Recall	F1_score
FT-ResNet	25%	24%	25%	24%
FT-ResNet+SVM	67%	63%	62%	62%
FT-ResNet+RF	81%	78%	74%	76%



Accuracy



Loss

Figure 7. Training Performance

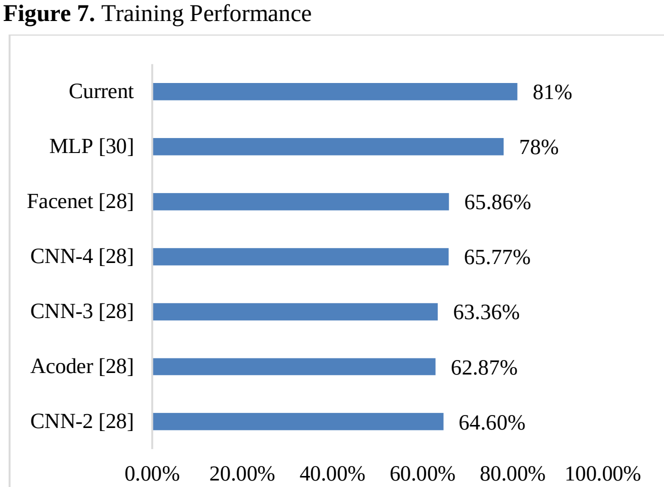


Figure 8. Comparative State of Art

The testing performance is presented in Table 1. In Table 1, three baseline models are presented i.e., Fine-tuned RseNet50 with softmax classifier (Model_1), Fine-tuned RseNet50 with SVM classifier (Model_2), and Fine-tuned RseNet50 with RF classifier (Model_2). Among these three-baseline models, maximum accuracy was achieved by Model_3 i.e., 81%. These results show that the performance of the presented model will be best suited for facial image-based personality detection. The comparative state-of-art is presented in figure 8. The fig is compared with some existing models implemented. In a report by M.A. Moreno-Armendariz et.al.[28], CNN models are proposed such as CNN-2, Acoder, CNN-3, CNN-4, and FaceNet, and achieved mean/average accuracy of 64.6%, 62.87%, 63.36%, 65.77%, and 65.86%.[29] Similarly, in X. Duan et.al.[30], the author presented MLP and achieved an accuracy of approx. 78%. Whereas, in our approach, the accuracy was achieved to be 81% which is the highest among all.

CONCLUSION

The paper presented a model for determining the facial-based personality prediction model. This model extracts the facial features to identify the personality trait. This work showed a model capable of predicting personality qualities from a portrait photograph, demonstrating that useful information may be obtained automatically without prior knowledge or interaction with a specific subject. The model has achieved an average accuracy of 81% which shows an improvement of 3% on state-of-art models. Therefore the following conclusion can be derived from the presented system:

- The model requires a single portrait for personality trait detection.
- The features are extracted automatically using deep learning models.
- Fine-tuning of the model improved the performance rate.

In the future, this work will be extended to more models to investigate their performance levels. In the future, the model will be extended towards a multi-modal system in which the personality questionnaires response will also be merged with facial features for more accurate prediction.

CONFLICT OF INTEREST: None

ACKNOWLEDGMENT: None

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