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Prediction of the Big Five Personality Traits Using Static Facial Images of College Students With Different Academic Backgrounds

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ABSTRACT Appearance can affect social interaction, which in turn affects personality development. There is ample evidence that facial morphology and social cues provide information about human personality and behavior. In this study, we focused on the relationship between self-reported personality characteristics and facial features. We propose a new approach for predicting college students' personality characteristics (on the basis of the Big Five personality characteristics) with static facial images. First, we construct a dataset containing 13,347 data pairs composed of facial images and personality characteristics. Second, we train a deep neural network with 10,667 sample pairs from the dataset and use the remaining samples to test (1335 pairs) and validate (1335 pairs) self-reported Big Five personalities. We trained a series of deep neural networks on a large, labeled dataset to predict the self-reported Big Five personality trait scores. This novel work applies deep learning to this topic. We also verify the network's advanced nature on the publicly available database with obvious personality characteristics. The experimental results show that 1) personality traits can be reliably predicted from facial images with an accuracy that exceeds 70%. In five-character tag classification, the recognition accuracy of neuroticism and extroversion was the most accurate, and the prediction accuracy exceeded 90%. 2) Deep learning neural network features are better than traditional manual features in predicting personality characteristics. The results strongly support the application of neural networks trained on large-scale labeled datasets in multidimensional personality feature prediction from static facial images. 3) There are some differences in the personality traits of college students with different academic backgrounds. Future research can explore the relative contribution of other facial image features in predicting other personality characteristics.

INDEX TERMS Computational and artificial intelligence, machine learning, face recognition static facial images, personality prediction.

I. INTRODUCTION

Since the time of the Greek philosopher Theophrastus (37–287 BC), people have been interested in the study of personality [1]. Personality is a psychological structure that is designed to explain various human behaviors through a small number of stable and measurable individual characteristic [2]. Taking the ''Big Five personality model'' as an example, ''love to make friends and be kind'' indicates the personality type of ''Extroversion; the individual characteristics of ''anxiety and emotional fragility'' indicate the personality type of ''Neuroticism''. A growing number of studies have linked facial images to personality. It has been established that humans are able to perceive certain personality traits from each other's faces with some degree of accuracy [3]–[7]. In addition to emotional expressions and other nonverbal behaviors that convey information about a person's psychological processes through the face, research has found that

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valid inferences about personality characteristics can even be made based on static images of faces with neutral expression [8]–[10]. The current research on personality prediction models has successfully predicted the relationship among ''thinking, emotion and behavior mode'' [15] and has a certain beneficial impact on important aspects of life [11] (including ''well-being, physical and mental health, interpersonal relationship quality, data, career choice, career satisfaction and professional performance, social participation, criminal activity and political ideology'' [12], [13]). These findings suggest that people may use signals from each other's faces to adjust the ways that they communicate, depending on the emotional reactions and perceived personality of the interlocutor. These signals must be fairly informative and sufficiently repetitive for recipients to take advantage of the information that is being conveyed [14].

The conclusion shows that there are several challenges to studying the relationship between facial image clues and personality traits. First, the previous research data set is not sufficient. There are few studies related to this issue in China and elsewhere, so it is difficult to obtain public experimental data sets. On the other hand, research in this field involves the personal data of participants, so the experimental data have privacy issues. Therefore, to carry out the research in this paper, we construct a new experimental dataset to study this problem. Second, existing studies use manual extraction of facial features to match facial features and personality traits. However, manually extracted features can lose valuable information related to personality, and the results cannot be applied to guide personality prediction.

The purpose of this study is to train a series of neural networks to predict personality characteristics from static facial images to study the correlation between facial images and the five personality characteristics of self-reported personality surveys. Our main contributions and innovations are described as follows: First, we constructed a new experimental data set (N = 13347) that contains static facial images and the corresponding self-reported personality traits. Second, a series of deep learning networks were trained on large, labeled data sets to train the prediction model, and a new personality prediction network was developed to improve the accuracy of personality trait predictions (the prediction accuracy for some dimensions exceeded 90%). Third, we conducted a pioneering study on the differences in personality traits and facial features of college students with different academic backgrounds.

II. DATA SET AND PREPROCESSING

A. SAMPLE AND PROCEDURE

The study was carried out in the Chinese language. The participants were anonymous volunteers recruited via social network advertisements. They did not receive any financial compensation but were provided with a free report on their Big Five personality traits. The data were mainly obtained from 14,107 college students (aged 18–25), including 5560 males and 8547 females. The data were collected online through a dedicated research website and a mobile application (app). Participants provided informed consent, completed questionnaires, reported their age and gender and were asked to upload photos. The images were required to show neutral, nonsmiling expressions, and the participants were asked to avoid facial cosmetics, jewelry and other decorations.

B. ETHICAL APPROVAL

Participants were asked for oral consent to participate in the study, and all data were collected after obtaining consent. The data from consenting participants were applied in this study. In addition, we numbered each subject, and the self-reported personality assessment data were collected anonymously in the form of numbers.

C. ESTABLISHMENT OF THE PERSONALITY DATA SET (BIG FIVE PERSONALITY)

The collected personality trait data, whether they were obtained via self-evaluation or an evaluation by others, should be evaluated on the personality assessment scale. Many scales have a large number of topics. To obtain the personality results, a single participant was evaluated for nearly an hour. Each sample needs to be separately evaluated according to the personality characteristics of multiple dimensions. The process is complex, slow and not highly accurate. Therefore, it is very difficult to obtain personality trait data; thus, few studies examine automatic personality prediction. We have performed a substantial amount of work on this topic. We use theBigFive personality theory [16], which is known as ''the leading paradigm in personality research and one of the most influential models in all psychology'' [17]. Researchers have reached a consensus on the personality description model. The five factors of the Big Five personality traits include neuroticism, extroversion, openness, agreeableness and conscientiousness. The five dimensions can be considered five scales. Each person's personality falls on a certain point within each scale. A point close to the endpoint means that an individual has certain preferences. The score values in each dimension fall within the range 0–60. For example, in the dimension of agreeableness, the higher the individual score is, the more easygoing and pleasant their personality is [18], [19].

For a specific content measurement, the simplified version [20] of the Big Five personality test scale, which was derived from NEO-PI-R and improved by Costa and McCrea, was selected. The scale applied in this study includes 60 questions on personal information and neuroticism, extroversion, openness, agreeableness and conscientiousness. The reliability of the scale that we used was tested with Cronbach's α coefficient. The results are shown in Table 1. The reliability of the five dimensions of the scale reached the level 0.6–0.80, which verifies the validity of the scale.

In this paper, the Statistical Package for the Social Sciences (SPSS) was used to analyze the related data. By the data

TABLE 1. Reliability index of the big five personality assessment scale.

Trait	Number of topics	Cronbach$^{\alpha}$
Conscientiousness	12	0.765
Openness	12	0.689
Agreeableness	12	0.834
Neuroticism	12	0.823
Extraversion	12	0.798

analyzed by SPSS 20.0, we can obtain the scores for each subject in the five dimensions (refer to Table 2 for a description of the Big Five personality traits of a tested person) and analyze the personality characteristics of each tested person according to their scores.

The initial sample consisted of 14,107 participants who completed the questionnaire and uploaded a total of 14,021 photos. The final consolidated data set consisted of 13,347 valid questionnaires and 13,347 relevant images (refer to photos). The ages of the participants ranged between 18 and 25 years old (62.1% were women with an average age of 21.4 years, and 37.8% were men with an average age of 20.7 years). The dataset was randomly divided into a training dataset (90%) and a test dataset (10%) to verify the prediction model. Additionally, we classified the participants into medical groups, engineering groups, literature groups, art groups and comprehensive groups according to their majors to explore whether the personality characteristics of the participants in different majors show certain regularity from facial features.

D. IMAGE AND PERSONALITY DATA SCREENING AND PREPROCESSING

1) CLASSIFICATION OF PERSONALITY DATA

According to the results of the Big Five test, each volunteer received five scores for the five personality trait dimensions, and the scores of each dimension were discrete numbers between 1 and 60. According to the different classification rules for the five characteristics (refer to Table 3), the personality scores of the different dimensions are divided into ''low, medium and high'' (such as low appropriate human nature, moderate suitable human nature and high appropriate human nature). Data analyses show that neuroticism, extraversion and openness are slightly unbalanced, and the distribution of pleasant and responsible data is relatively balanced. This trend is generally consistent with the personality characteristics of people from Asian countries because there are few people with high openness, high neuroticism and low extraversion. To facilitate analyses, we binarize the personality characteristics data. Therefore, according to the distribution of the scores of each personality trait, we divided each trait into two categories. The first category indicates that the personality trait is more obvious, and the second category indicates that the personality trait is not obvious. (Taking neuroticism as an example, neuroticism is more significant when the score is higher than 38.8.) The final classification attributes are shown in Table 4.

2) IMAGE SCREENING AND PREPROCESSING

After screening, we removed false and low-quality facial images and manually adjusted the remaining images to remove partially covered facial images. These images were either processed by Photoshop or were false images without surface features detected with computer vision (CV). The network input layer requires fixed-size data, so the sample was normalized to have a fixed size during training. The analysis of sample data shows that the sample images are square with an edge length of M pixels. The edge lengths of all images are measured, and the median of the edge length is 114 pixels. Therefore, we applied the face and eye detection, alignment, sizing, and clipping features available in Dlib (dlib.net) and obtained a set of 112×112 pixel images.

After combining the selected questionnaire answers and pictures, we obtained a group of 13,347 valid questionnaires and 13,347 valid images.

III. DESIGN AND TRAINING OF THE PERSONALITY PREDICTION NETWORK

In this work, the traditional back propagation (BP) network is compared with the deep learning network, and an improved personality classification prediction network is proposed. In this study, a 50-fold cross validation method was applied to analyze the effect. The data were randomly divided into five parts, one of which was selected as the verification set and the remaining four were selected as the training set. The average of the five validation results was applied as the final result. The number of training sets was 10,677, and there were 1335 test sets and 1335 verification sets. To solve the unbalanced sample problem, cost sensitivity, focal loss, upsampling and data enhancement are considered in the training.

In existing studies, researchers usually design a set of features (geometry, texture, color, global appearance features, etc.) according to the heuristic criteria to describe the correlation between a face and personality [21]–[28], but these features are not comprehensive enough. To more comprehensively express the information contained in a facial image, a facial image pyramid is constructed, and the texture features of the whole face at full scale are extracted. The BP network is used to learn and predict whole face texture features. The classic BP network structure is selected to train the five types of personality data according to the two previously agreed-upon classification criteria. The input image size of the network is $112 * 112$ pixels, and the network adopts the structure of the input layer + hidden layer + output layer.

After training, the prediction results on the test set are shown in Table 5. The training results based on the BP neural network can accurately predict neuroticism and extroversion, but the prediction results of openness, agreeableness and responsibility are not ideal.

We expect that personality traits are reflected in the whole facial image rather than in isolated features. Based on this expectation, we hope to extract advanced features from

TABLE 2. Big five personality traits descriptions.

Low neuroticism	**Rational**	**Stability**	**Sensitive**	**High neuroticism**
Calm, dull, safe, guiltless	<20.4 points		>38.8 points	Excited, alert, reactive
Low extraversion	**Introversion**	**neutral**	**neutral**	**Highly extroverted**
Conservative, independent, incommen surable	<26 points		>42 points	Enthusiastic, sociable, enthusiastic
Low openness	**Conservative**	**moderate**	**open**	**High openness**
Introverted, conservative, professional	<32 points		>47 points	Hobbies, pursuit of new ideas, freedom, passion
Low agreeableness	**Aggressive**	**Mediation**	**Accommodated**	**Highly pleasant**
Attacking, unfriendly, distrustful, ske ptical	<32 points		>47 points	Cooperative, inclusive and modest
Low conscientiousness	**Not concentrated**	**Balanced**	**concentrated**	**High conscientiousness**
Spontaneous, divergent, unorganized	<32 points		>47 points	Organized, planned, and cautious

TABLE 3. Statistical table of data classification.

category	Trait (numbers)				
	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness
low	29	18	6328	7934	5043
medium	12,861	10081	7019	5413	8226
high	457	3248	0	0	78
total	13,347	13,347	13,347	13,347	13,347

Number of high, medium and low categories in the five personality attributes.

TABLE 4. Two classification statistics of personality data.

category	Trait (numbers)				
	Neurotici	Extraversion	Openness	Agreeablenes	Conscientiousnes
not obvious	12861	10081	6328	7934	5043
more obvious	486	3266	7019	5413	8304
total	13347	13347	13347	13347	13347

images based on a deep learning method for character prediction. We use two well-performing and widely applied deep learning networks to classify personality traits. The selected classification methods are MobileNetv2, ResNeSt50 and the improved deep learning network, which is the personality prediction neural network based on soft thresholding (S-NNPP). The training in this section is fine-tuned using the ImageNet pretraining model. The optimization strategy is random gradient descent, the initial learning rate is 0.001, and the learning rate optimization strategy is ReduceLROnPlateau. ReduceLROnPlateau can dynamically adjust the learning rate according to the loss. Random flipping, Gaussian noise, random contrast adjustment, random brightness adjustment, and $-15°$ and $15°$ random rotations were added to enhance the data.

A. LIGHTWEIGHT CONVOLUTIONAL NEURAL NETWORK: MOBILENETV2

MobileNetv2 is a classic lightweight neural network. The following uses MobileNetv2 to train the five attributes. The depths of 112 learning frames are used for open source learning (Caffe deep learning).

The experimental results in this section are shown in Figure 1. By the comparison in Table 4, the prediction effect of the deep learning network based on MobileNetv2 is significantly higher than that based on the BP neural network. Especially for the relatively balanced data, openness, agreeableness and sense of responsibility, the prediction accuracy is improved significantly.

1) DEEP RESIDUAL NETWORK: ResNeSt50

ResNeSt, which was proposed in 2020, can be regarded as a ''synthesizer'' standing on giants. The excellent performance of ResNest in ImageNet image classification also reflects the network's adaptability to classification tasks. In this step, we use the ''simple and practical'' deep residual network, ResNeSt50, which has stronger network capabilities for classification prediction. The ResNeSt model was employed to fine-tune the five kinds of data [29]. The experimental results show that the classification accuracy for the five categories is better than that of MobileNetv2. In particular, the prediction accuracy for extroversion, amenities and responsibility is greatly improved (refer to Figure 2).

2) IMPROVED NEURAL NETWORK FOR PERSONALITY PREDICTION (S-NNPP)

To improve the prediction performance, we developed a deep neural network, S-NNPP, based on an attention mechanism. Our goal is to select a neural network structure with good

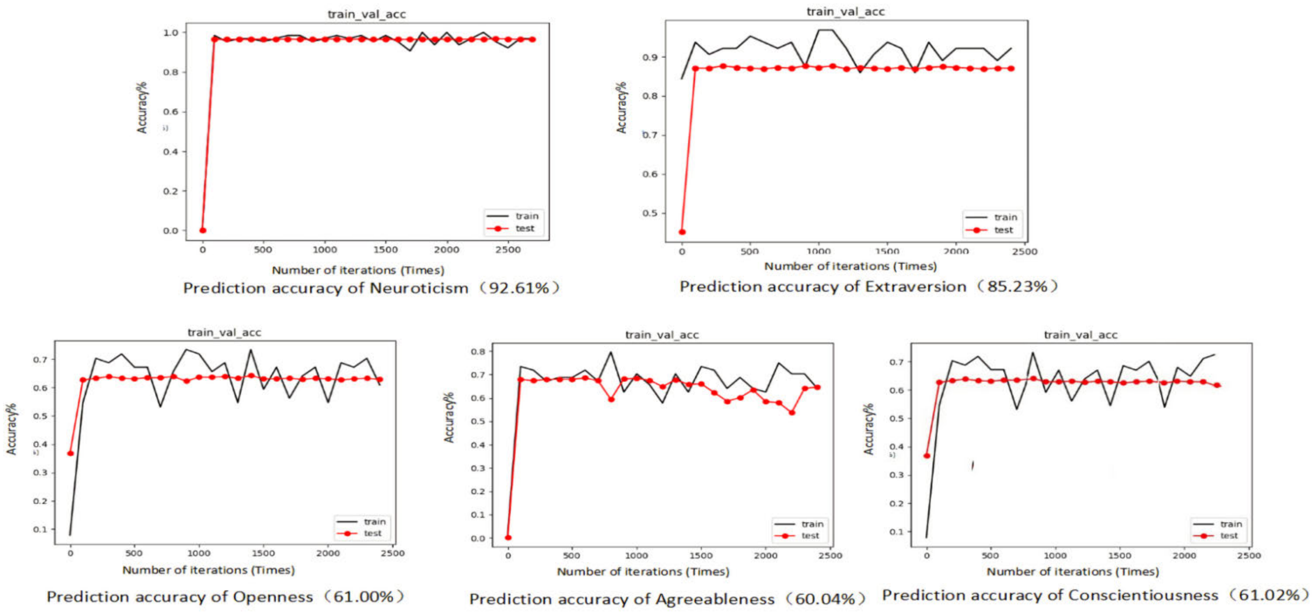

FIGURE 1. **The figure shows the prediction accuracy for the five personality attributes trained by MobileNetv2. The prediction accuracy of MobileNetv2 is significantly higher than that of the traditional BP network.**

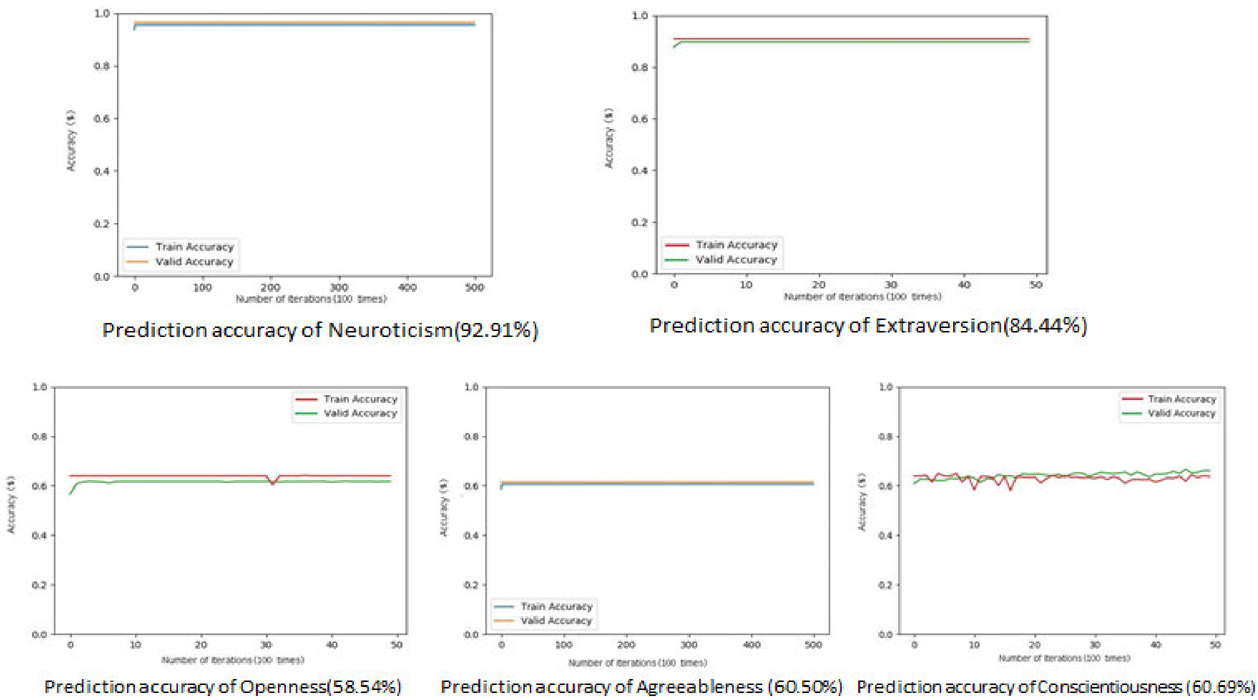

FIGURE 2. **The figure shows the prediction results for the five kinds of data after pretraining with ImageNet and the ResNeSt50 model.**

image classification performance for multiscale image feature extraction. ResNeSt's excellent performance in ImageNet image classification also reflects the adaptability of the network to classification tasks. We use ResNeSt's basic module to improve the following network.

As seen from the network diagram, the network replaces the $3 * 3$ convolution in ResNeSt with packet convolution via splitting. Additionally, multiple branches are used to perform attention. Here, packet convolution is performed in each path. Each result of the group convolution is fused after the softmax operation. The network structure of ResNeSt is detailed as follows:

In this study, soft thresholding [25] was introduced to improve the adaptability of the model to noisy data. Soft thresholding is a common signal denoising method. Through soft thresholding, the features whose absolute values are

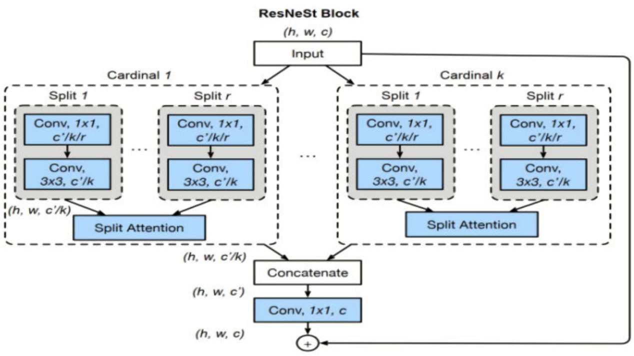

FIGURE 3. Network structure of ResNeSt.

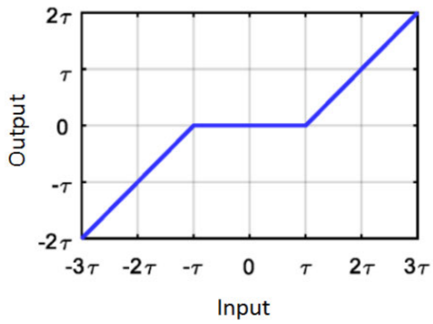

FIGURE 4. Soft thresholding curve.

lower than a certain threshold are set to zero, and the other features can be adjusted to zero. The introduction of soft thresholding in ResNeSt can reduce the interference of redundant information in datasets on network learning.

The soft thresholding formula is expressed as follows:

$$soft(x, T) = \begin{cases} x + T(x \le -T) \\ 0(|x| \le T) \\ x - T(x \ge T) \end{cases}$$

In the formula, | x | is the coefficient of the wavelet transform, and T is the preselected threshold.

The curve corresponding to the formula is defined as follows

It can be seen from the formula and graph that soft thresholding can delete the data beyond threshold T and compress the data within threshold t. In the network, the important features can be compressed and preserved, and the unimportant features can be deleted. In practice, the redundant information content in different samples is often different. Therefore, it is necessary to set different thresholds for different samples. Therefore, a subnetwork is added to the basic network to obtain a set of thresholds for soft thresholding on the feature graph. In this way, each sample can obtain a set of unique soft thresholding thresholds to remove redundant information. The modules of the altered network are depicted as follows:

The network structure of the soft thresholding module is shown as follows:

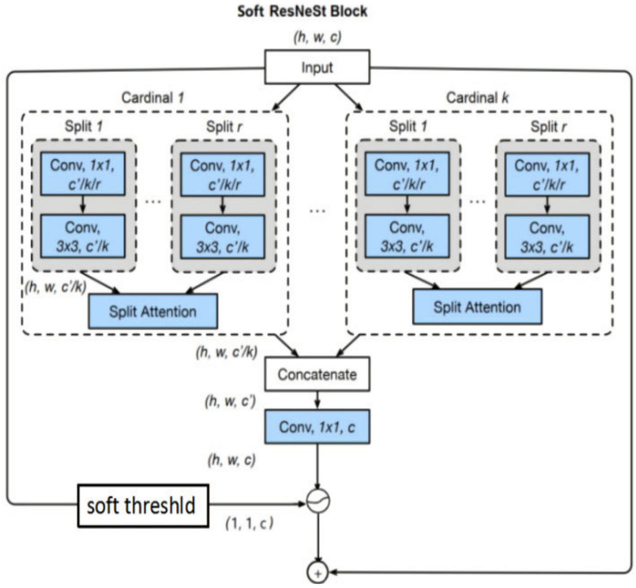

FIGURE 5. Basic network module after adding a soft thresholding module.

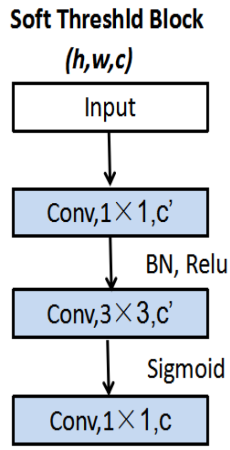

FIGURE 6. Network structure of soft thresholding module.

The main body of the Soft_ResNeSt network adopts a double branch structure: one branch inputs the whole image, and the other branch inputs the face area. The open source face detector software OpenCV is used to obtain the face region. The improved ResNeSt module is applied in the basic modules of the two branches, and the prediction results of the two branches are fused with parameter α. The overall network structure is detailed as follows

B. SUMMARY

In this section, the lightweight MobileNetv2 network is used to classify and predict personality data. The classification results have a good effect on neuroticism and extraversion but a poor effect on openness, agreeableness and sense of responsibility. The complex network ResNeSt50 is selected for classification prediction, and the result is slightly improved, which indicates that the complex network can extract more relevant deep features. Combined with ResNeSt and soft thresholding, we propose a new prediction network

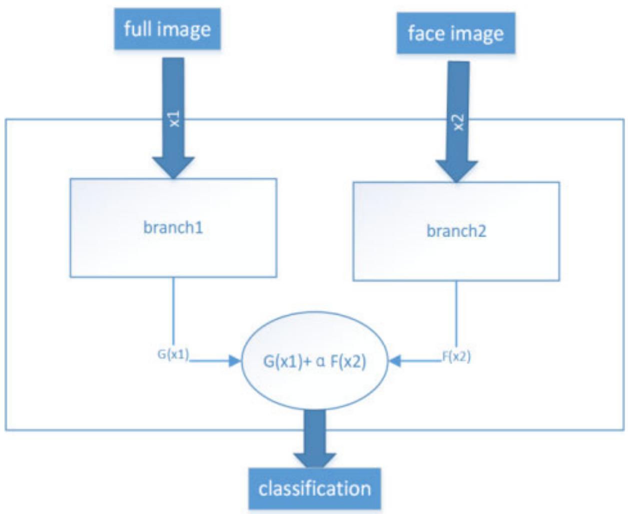

FIGURE 7. Overall network structure of S-NNP.

(S-NNPP). The prediction accuracy of the proposed network for the five personality dimensions is significantly improve, which also shows the superiority of the S-NNPP network performance.

IV. RESULTS

A. PREDICTION ACCURACY

In this paper, we randomly divide the data into five parts, select one part as the verification set and select the remaining four as the training set. We employed data from the separate validation dataset, which contains1335 facial image prediction scores that correspond to 1335 individuals. The average of the five validation results is applied as the final result.

We tested the accuracy of different networks for the five personality traits. Table 5 shows the classification accuracy of the four networks for the five personality traits. For these classification accuracy rates, the reliability of these results is verified by calculating the confidence interval, and the results are shown in the data in brackets.

The results show that neuroticism (emotional stability) and extraversion are more easily identified than the other three features (recognition rate greater than 90%). The recognition degrees for openness, agreeableness and responsibility are relatively weak, but they also significantly exceed the 50% expected by chance. This finding is slightly different from existing findings [10], [16]. This result reflects the notion that all of our volunteers are from Asian countries. In contrast, people from Western countries highlight their ''openness'', ''agreeableness'' and ''sense of responsibility'', whereas these traits in people from Asian countries are weaker. We found that this study, which did not involve any subjective human ratings, constitutes solid evidence that all the Big Five traits are associated with facial cues that can be extracted through machine learning algorithms. However, although we have adopted a reasonable structure and technology for applying static frontal facial images to predict personality traits, we still cannot claim that the deep facial morphological features extracted with a deep learning network can reflect all personality-related factors. In contrast, we suggest that the profile images of subjects should also be utilized to determine whether profile information can contribute to the prediction of personality (subsequent studies will include an analysis of profile images).

B. DISCUSSION

Through our work, new evidence shows that static facial images are related to personality characteristics. We expect that machine learning (in our case, the improved deep learning network S-NNPP) can reveal five-dimensional personalized features based on static facial features. By developing a deep neural network and training it on a data set with self-reported Big Five personality traits, we avoid the reliability limitation of human ratings.

We expect that personality traits are reflected in the whole facial image rather than in isolated features. Therefore, we abandoned traditional manual feature extraction [20], [22], [30]–[32] and employed a deep learning network. Based on this expectation, we developed a new attention-based personality prediction network (S-NNPP), which combines ResNeSt and soft threshold S-NNPP, to improve the prediction accuracy.

Our results show that real images taken in uncontrolled conditions can be used with sophisticated computer vision algorithms to predict personality traits. This finding contradicts the findings of previous studies, which relied on high-quality facial images taken in controlled environments. Our prediction accuracy was higher than the prediction accuracies of previous studies (the best prediction was 58%) [33], [34] and used real personal images taken in uncontrolled conditions. The advantage of our method is that it is relatively simple and fast and can be easily implemented via desktop computers.

C. NETWORK EFFECT VERIFICATION

To verify the effect of the network, we use a publicly available database with obvious personality characteristics to verify the S-NNPP network. The experimental data were collected from the public portal personality first impressions dataset. The dataset contains a total of 30,935 images from 8000 videos with five personality traits. The personality score is also based on the Big Five personality traits, which are assessed by professionals, with a score of 0–1.

The scores in the data set are continuous, so this experiment also uses regression to predict the scores. The experimental images are divided into a training set, test set and verification set according to an 8:1:1 video tag. The training set consists of all the images from $8000 * 0.8$ videos of 30,935 images. In the experimental results statistics, all the images from the same video are predicted, and the average value is taken as the final prediction score.

The branch input of the network full image is the size of the whole image resizing to 224×224, and the branch input of the face area is the size of the face area resizing to 224×224

TABLE 5. Prediction performance comparison.

Trait	Traditional BP(%)			MobileNetv2(%)			ResNeSt50(%)			S-NNPP（%）		
	TPR	FPR	F1	TPR	FPR	F1	TPR	FPR	F1	TPR	FPR	F1
Neuroticism	80.00	3.28	87.55	85.93	3.03	90.98	87.41	1.52	92.55	92.91	1.43	96.55
Extraversion	72.48	6.78	81.51	75.52	6.45	83.40	76.51	1.69	86.04	84.44	1.52	91.84
Openness	47.24	40.00	49.38	49.59	38.36	50.63	54.14	32.84	57.83	58.54	30.56	62.25
Agreeableness	44.59	45.45	50.54	55.12	35.71	56.68	55.81	34.78	57.83	60.50	32.43	63.25
Conscientiousness	41.29	50.00	46.55	54.42	33.33	59.93	58.39	30.77	62.26	60.69	26.23	65.42

We applied the true positive rate, false positive rate and F1 score to evaluate the prediction performance of the model. The BP neural network is the most traditional neural network. MobileNetv2 and ResNeSt50 are deep learning networks. S-NNPP is our improved personality prediction deep neural network based on an attention mechanism. The forecast results are expressed in terms of "%".

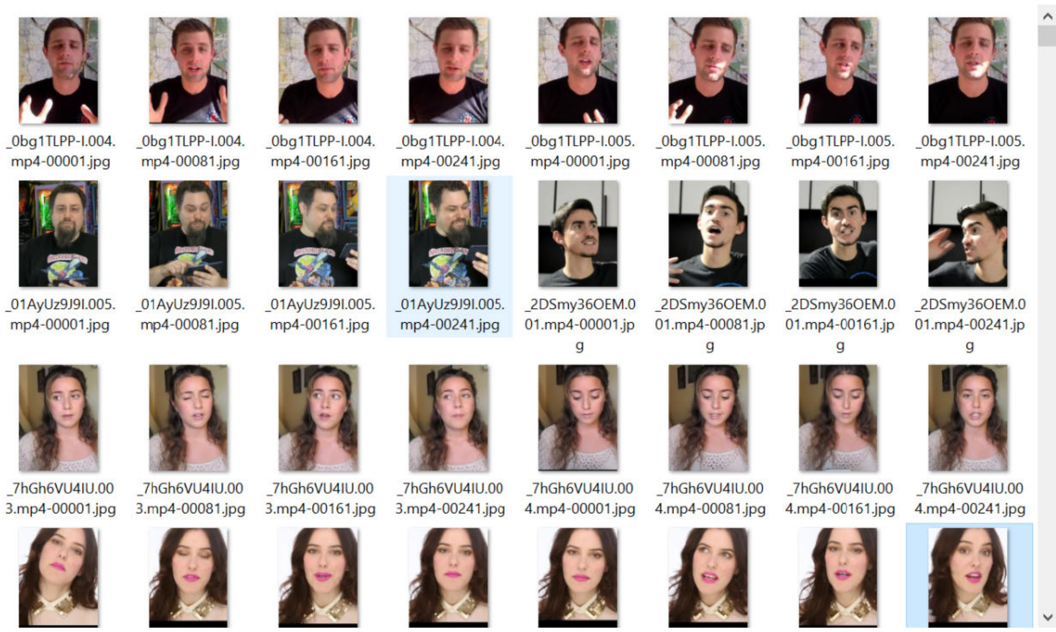

FIGURE 8. Sample dataset of portrait personality first impressions.

detected by OpenCV. The random gradient descent algorithm is utilized for network training. The momentum is set to 0.9, the batch size is 64, the initial learning rate is 0.1×10^{-4}, the weight attenuation is 10^{-4}, and the learning rate attenuation is 0.5.

The statistical formula of prediction accuracy is expressed as follows

$$S = 1 - \frac{\sum_{i=1}^{N} \left| t_i - p_i \right|}{N}$$

In the formula, N is the number of test videos, pi is the prediction score of the ith video, and ti is the marking score of the ith video.

Table 6 shows that, unlike other methods, this paper does not use only portrait features or full image features but fuses portrait features and full image features, which is more helpful in mining deep features for personality prediction. The S-NNPP algorithm with the softleshld module still has some advantages in extraversion and agreeableness prediction without fusing audio features, while the accuracy of the other three personality predictions is only slightly decreased, which shows the effectiveness of the algorithm.

D. APPLICATION

A person's personality traits identified from real-life facial images can be widely utilized in many applications. In daily social affairs, the personality type of an individual is very useful. Our model complements traditional personality assessment methods. Personality prediction based on

TABLE 6. Prediction performance comparison.

Network	Average	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
S-NNPP	0.9134	0.9152	0.9129	0.9168	0.9099	0.9121
ResNeSt50	0.9110	0.9121	0.9112	0.9131	0.9088	0.9100
NJU-LAMDA	0.9130	0.9133	0.9126	0.9166	0.9100	0.9123
evolgen	0.9121	0.9150	0.9119	0.9119	0.9099	0.9117
DCC	0.9109	0.9107	0.9102	0.9138	0.9089	0.9111
ucas	0.9098	0.9129	0.9091	0.9107	0.9064	0.9099
BU-nku	0.9094	0.9161	0.9070	0.9133	0.9021	0.9084

TABLE 7. Analysis of prediction results of professional groups.

Subject grouping	Number of volunteers	Accuracy (%)														
		Neuroticism			Extraversion			Openness			Agreeableness			Conscientiousness		
		TPR	FPR	F1	TPR	FPR	F1	TPR	FPR	F1	TPR	FPR	F1	TPR	FPR	F1
engineering	2911	91.40	1.23	94.74	83.91	6.25	87.61	53.39	31.25	55.75	52.82	30.46	56.90	63.01	27.78	60.58
medicine	1889	96.02	6.59	95.00	92.18	9.09	92.09	76.05	36.36	67.08	69.96	39.62	63.42	75.42	37.50	65.57
artistic	1878	94.31	5.41	96.82	86.08	3.03	91.07	59.36	30.30	62.80	56.04	32.26	60.89	55.17	28.00	64.17
comprehensive	6669	94.25	5.75	94.62	94.73	12.50	91.24	69.64	43.10	58.21	71.63	42.37	58.89	75.88	38.60	64.44
total	13347	92.91	1.43	96.55	84.44	1.52	91.84	58.54	30.56	62.25	60.50	32.43	63.25	60.69	26.23	65.42

facial features has broad application prospects in digital entertainment, social networks and software development. The research and application of virtual humans is a becoming a popular research topic. Personality matching based on facial features will also become the mainstream function of various social networking, job hunting and online dating websites and can quickly recommend a target face [28] to users in accordance with the selected range. In addition, research on facial personality prediction can also provide support for criminal tracking [35] and face-based target employee selection.

Our research is based on college student; so in terms of application scenarios, it can assist college students in searching for jobs by matching their personalities, which has reached ‘‘person job matching’’. This technology can be applied to enterprise recruitment and rapid analysis of employees’ personality, can assist employers in interviewing employees, and can be applied to students’ online counseling and other auxiliary functions, which are not completely recommended ‘‘know people’’ by artificial intelligence.

To further verify our experimental results, we also built a new data set for experimental analysis. This data set contains two groups of facial images, each of which is a positive expressionless bareheaded photo of the corresponding sample collected by the research group. The categories of these two groups of images are students who have obtained examination-free postgraduate qualifications and students who have dropped out. Each group contains 8 facial images.

For the samples of these two categories, some of them have excellent results and strong scientific research ability, and some of them have failed in many subjects or have dropped out of school due to disciplinary action. Therefore, we have a general understanding of some aspects of their personality traits. On the other hand, because the samples of the same category have some of the same behavior performance, the personality traits of these individuals can be compared. There is a certain similarity in energy. We use theS-NNPP network to verify these results, and the experimental results show that the samples of the same category have some similarities in personality traits. For the eight excellent students for which we collected data, the classification model predicts that their sense of responsibility and agreeableness are more significant, and some excellent students show a strong openness. For students who dropped out, their neuroticism is generally higher, and there is no obvious commonality in other dimensions.

V. INFLUENCE OF A SUBJECT BACKGROUND ON PERSONALITY CLASSIFICATION

We employed the improved personality prediction network (S-NNPP) to predict the personality traits of subject groups according to their different academic backgrounds. The prediction results are shown in Table 7.

The data are divided into four groups according to the backgrounds of the students, namely, engineering, medicine, art and synthesis. The prediction results for the five characteristics of the four groups of data are analyzed. The prediction results for the medical group for the extrovert, pleasant and responsible categories are slightly higher than average, which is consistent with existing research. The relevant research shows that medical practitioners have more extroverted personalities, which include the characteristics of optimism, good communication and a strong sense of responsibility [16], [36]. The prediction results for the art group for neuroticism and openness are slightly higher than average. Previous studies show that artists are open-minded and imaginative and have great emotional fluctuations [37], [38]. Data from the other background groups do not present any special rules.

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