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ANALYZING EVALUATING PERSONALITY AND HUMAN BEHAVIOR BASED ON FACIAL INDEX AND BIG FIVE MODEL

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Abstract. Numerous studies have shown that morphological and social indicators in a human face can provide information about a person's personality and behavior. The Big Five model, also known as the Five-Factor, is the five basic dimensions of personality. These dimensions include openness, conscientiousness, extraversion, agreeableness and neuroticism. The Big Five model has been applied in a variety of different settings, including clinical psychology, organizational psychology, and even marketing research. By examining where an individual falls on each of these dimensions, researchers can gain insight into their unique personality traits and use this information to make predictions about their behavior and performance in different situations. In our existing iscv platform, a job searching website, we can help employers better understanding employee incentives by utilizing the personality traits information of candidates. Managers and CEOs can therefore discover a means to improve relationships and communication while also managing and building teams more effectively. We trained a machine learning model using a hybrid CNN-LSTM, ResNet, VGG19 algorithm for personality recognition through interview video. In each video, we analyze facial movement by using the 3D landmarks extracted with the 3DDFA-V2 algorithm. The model uses the UDIVA v0.5 dataset, collected in the scope of the research project entitled "Understanding Face-to-Face Dyadic Interactions through Social Signal Processing". The experimental results conclude: (i) Analyzing facial movement by using the 3D landmarks extracted with the 3DDFA-V2 algorithm. (ii) Personality traits inferred from facial behaviors by most benchmarked deep learning model. (iii) Personality assessment model is trained from a combination of two data sets (one UDIVIA dataset and one self-survey dataset) to fit Asian personalities. (iv) The detailed Big Five personality tendency assessment table is based on the interview video and questionnaire of the surveyed people.

Keywords. Big Five, personality traits, CNN-LSTM, ResNet, VGG19, UDIVA dataset, facial landmarks.

1. INTRODUCTION

The development of automation, enabled by a combination of robotics and artificial intelligence, has already had a significant impact on the way work is done across industries.

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In addition to the work of improving productivity, technological advancements have also led to a significant improvement in helping businesses find human resources with high skills and personalities suitable for the work environment. It can also bring about more job opportunities, as companies that invest in automation often require a highly skilled workforce. Nowadays job opportunities are a hot topic among young people, especially in the context of the economic crisis. Many job search platforms were born to be the connection between businesses and applicants. From the perspective of the business, they want to find the most suitable candidates, understand the skills and personalities of the candidates in the most optimal time. From the perspective of applicants, they want to find many working opportunities from there to determine a job that is most suitable for them. Understanding personality is essential to comprehending human internal and external states. Therefore, we have conducted research to create a model to analyze and evaluate human personality based on the Big Five model. From there, we integrated into the ISCV employment support system to help businesses evaluate candidate personalities and simplify the recruitment process. In this paper, we present a fair and consistent evaluation of seven standard deep learning models and the personality traits are based on the Big Five model. Pre-existing research papers use the UDIVA dataset to train the model. In our research model, we combine the UDIVA dataset and the dataset we conducted our own survey based on the facial shape of Asians in general and Vietnamese people in particular to increase the applicability of the model.

Therefore, we trained a model to assess one's own personality traits when considering career paths to ensure a good match between one's strengths and the demands of the job for our job searching platform ISCV through their interview video. The Big Five model, also known as the Five-Factor model. This model is based on five key traits that are believed to be universal across all individuals. These traits include openness, conscientiousness, extraversion, agreeableness and neuroticism. Conscientiousness describes a person's capacity to manage impulse control so that they can engage in conduct that has a purpose. It gauges characteristics of behavior like control, restraint, and persistence. Agreeableness refers to how people tend to treat relationships with others, contrary to extraversion, which consists of pursuing relationships, agreeableness is more concerned with how people behave and interact with others. Neuroticism stands for a person's overall emotional stability in terms of how they view the world. It considers a person's propensity to see things as threatening or challenging. Openness to experience refers to one's willingness to try new things as well as engage in imaginative and intellectual activities. It includes the ability to "think outside of the box". Extraversion reflects the tendency and intensity to which someone seeks interaction with their environment, particularly socially. It includes a person's level of comfort and assertiveness levels of people in social situations. Each of these traits is further broken down into subcategories, allowing for a more nuanced understanding of a person's personality. The system will use Artificial Intelligence (AI) to evaluate and analyze users' personalities, thereby offering jobs that suit their needs and interests. To analyze a person belongs to which of five personality traits through an interview video, we first extract frames from the interview video and obtain 3D landmarks of facial points by using 3DDFA-V2 algorithms. Then, facial landmarks data will be processed through features extraction step. After that, we use processed features to train a ResNet model, a VGG19 model, a hybrid CNN-LSTM and compare results with several algorithms including Random Forest Regression, Linear

Regression, CatBoost Regressor, LSTM. Our team also conducted a Big Five survey with more than 100 volunteers to collect data. The interview is conducted through an online meeting, and the interviewees will in turn introduce themselves and answer the Big Five questionnaire. After collecting data, these will be included in the model to evaluate calculations and return results. We took the data fed into the visual model and the Big Five model to give the final five personality traits results and turn out a report. The whole execution is done in the Python programming language. This system will be upgraded with the use of Blockchain technology to ensure data security and transparency, thereby helping to minimize cases of certificate forgery and increase authenticity accuracy in the process of recommending jobs that match the user's personality. Furthermore, the system allows employers to find and connect with students with skills and abilities that match their needs. This will help users access jobs that suit their abilities more easily and quickly. In this section, we focus on building the Big Five system along with developing the ISCV job search support platform system in the previous section. The subsequent sections comprise the remainder of this paper. Section 2 introduces the big five traits and analyzing the facial movement method. Section 3 details the process of research methodology including the big five personality survey and the process in visual model. Section 4 discusses the experimental results of the proposed method. Finally, Section 5 concludes the paper.

2. RELATED WORK

2.1. The Big Five traits

Understanding the relationship between personality characteristics and academic motivation may be central to developing more effective recruitment strategies. This research [1] examined the relationship between the Big Five personality traits and individual differences in college students' academic motivation. Individuals (172 undergraduates) were asked to complete the NEO Five Factor Inventory (Costa - McCrae, 1992) and the Academic Motivations Inventory (AMI; Moen - Doyle, 1977). Results revealed a complex pattern of significant relationships between the Big Five traits and the 16 subscales of the AMI. Results are interpreted in terms of creating an proper fit between teaching modalities and individual differences in students' academic motivation due to personality traits.

Recent political science research on the effects of core personality traits the Big Five – contributes to our understanding of how people interact with their political environments. This research examines how individual-level variations in broad, stable psychological characteristics affect individual-level political outcomes. In this article [2], they review recent work that uses the Big Five to predict political attitudes and behavior. They also replicate some of these analyses using new data to examine the possibility that prior findings stem from sampling error or unique political contexts. Finally, they discuss several of the challenges faced by scholars who are currently pursuing or are interested in pursuing this line of inquiry. These challenges include refining theoretical explanations of how the Big Five shape political outcomes, addressing important measurement concerns, and resolving inconsistencies across studies.

2.2. Identifying the Big Five personality by analyzing the facial movement

Research [3] proposed method to automatically identify the Big Five personality traits by analyzing the facial movement in ordinary videos. Through the correlation analysis between facial features and personality scores, they found that the points from the right jawline to the chin contour showed a significant negative correlation with agreeableness and the movements of the left cheek's outer contour points in the high openness group were significantly higher than those in the low openness group. By using asynchronous video interview (AVI) processing and a TensorFlow AI engine, research [4] developed an end-to-end AI interviewing system to perform automatic personality recognition (APR) based on the features extracted from tracking 68 facial landmarks in the AVIs and self-reported questionnaires of 120 real job applicants. Research [5] investigates the association between personality traits and facial attributes. A facial image-based computational personality traits classification is conducted to verify the connection between facial attributes and personality traits. Their one-factor classification results show that personality traits conscientiousness and neuroticism are significantly associated with extracted facial attributes. Furthermore, the two-factor classification results show that the personality traits with higher heritability have more concrete association with internal facial features. Many studies recently are using facial landmarks to extract the features, so that they can develop an automated personality recognition model. To provide a fair and consistent evaluation of eight existing personality computing models (such as audio, visual, and audio-visual) and seven standard deep learning models on both self-reported and apparent personality recognition tasks, research [6] proposed. Research [7] presents the first systematic comparison of state-of-the-art approaches for behavior forecasting. They accomplish this by utilizing face-to-face dyadic interaction-supporting whole-body annotations (facial, body, and hands) from the recently released UDIVA v0.5. Research [8] provide the first benchmark test set for multi-modal information processing and to foster collaboration among the audio, visual, and audio-visual affective computing communities, to compare the relative merits of the approaches to automatic appropriate facial reaction generation under different spontaneous dyadic interaction conditions. This won't have disadvantages of text and image identification which requires users to report their private information and takes time. In this paper, we take advantage of the results on personality traits of the Big Five model in previous studies and apply it to analyze on the UDIVA data set (a data set that records personality traits). and human facial movements to infer personality). Not only that, we have applied geometric calculations to calculate the rotation direction of the face and used deep learning algorithms to train the model and provide the most accurate results.

3. RESEARCH METHODOLOGY

The research method proposed in this paper includes the following main processes: Big Five personality survey, visual model, Big Five proposal formula, and Big Five summary. First, we conducted the Big Five personality survey to collect the personality data of each person. Next, the data set is entered as input data, and performed experiments and calculations to return the results of each person's personality score through visual model and the Big Five proposal formula. Then, aggregate the score results from Visual Model with the Big Five proposal formula and return the Big Five summary. The flow chart of our research

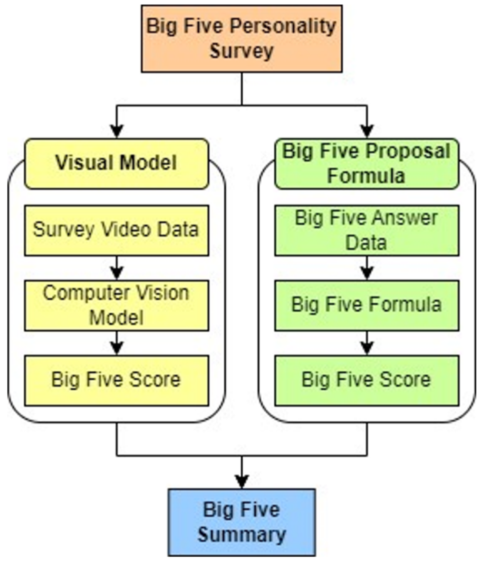


Figure 1: Process diagram of the research methodology

method is shown in Figure 1, and the implementation and experimental research will be described below.

3.1. Big five personality survey

In this process, we researched, collected data from many sources including survey sites, scientific articles on Big Five research and synthesized them into a set of Big Five questions (including 50 questions with 10 sentences for each personality) to assist in conducting the survey. At the same time, we also researched and decided to use BFI (Big Five Inventory) Scale to divide the response score for each Big Five question. The BFI assesses the Big Five domains (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) that the respondent answers on a five-point rating scale, ranging from 1 to 5 with the meaning of each level as follows: 1 - disagree, 2 - slightly disagree, 3 - neutral, 4 - slightly agree, 5 - agree [9]. We then mobilized more than 100 volunteers to do this test by recording the interview video (volunteers were asked to open the camera and micro during the interview). The video interviewing the Big Five survey consists of two parts as follows:

- Part 1: Volunteers will have a minimum of 30 seconds - a maximum of 1 minute to introduce themselves (name, occupation, hobbies,...).

- Part 2: The interviewer will ask each question in the collected Big Five questionnaire and the volunteer will answer from 1 to 5 based on the BFI Scale. During the video recording process, the interviewer will record each answer score for each question.

After finishing the Big Five survey, we collected a data set including mp4 (moving pictures expert group 4) files containing the interview video and txt (text file) files having the response scores of the Big Five questionnaire. The data set was fed into the next 2 processes, Visual Model and Big Five proposal formula, to calculate the score of each personality in the Big Five model.

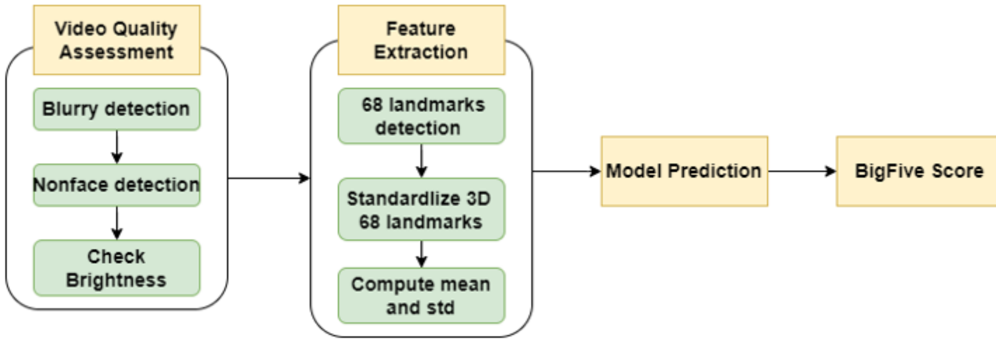


Figure 2: Process in visual model

3.2. Visual model

In this section, we performed two processes which are feature extraction and video quality assessment. To begin with, feature extraction is the process of extracting relevant and useful information from a video, such as color, texture, and motion. This information can then be used to identify objects, track movement, or detect anomalies. On the other hand, video quality assessment is the process of evaluating the quality of a video. To assess how well the video works, many video quality measures are looked at, including sharpness, brightness, and resolution. This procedure is essential for making sure the video satisfies the specified quality requirements and is proper for the purpose for which it is intended. As such, the two processes are essential steps in video analysis and play a crucial role in ensuring that the final product is of high quality.

Video quality assessment

First, video will be evaluated through the quality evaluation steps. Every frame, we detect sequentially with 3 factors include blurry, non-face, dark. To ensure correct detection, our system scans each frame using a three-factor sequential detection process.

Step 1: We begin by checking for blurriness in the frame, which could be caused by any number of factors such as camera shake or low light conditions. If the frame meets a blurry standard, it will be evaluated in the next steps. To evaluate whether frames are blurred or not, we use OpenCV library to calculate variance of the Laplacian index [10]. If the variance of the Laplacian index is lower than threshold 100, frame will be considered blurry, else we continue to step 2.

Step 2: Next, we check for the presence of non-faced objects in the frame, such as a nearby tree or a passing car, which could interfere with correct detection of the target object. To detect a face within a frame, we utilize FaceBoxes [11] for face detectors. This detector has superior performance on both speed and accuracy. If there is no face detected, the frame will be considered non-faced. However, if a face is detected, then we can move on to the next step in the process.

Step 3: Finally, after detecting the face in frame, we assess the overall darkness of the frame, as a low-light environment could also hinder detection accuracy. By calculating the mean color index of frame, if this index of frame is lower than 0.35, facial frame will be considered as dark.

Feature extraction

In this work, the extracted facial frame after assessing quality will be used to extract features by analyzing facial landmarks movement. Each landmark point will contain 3-dimension (x, y, z) value, this helps analyze movement of landmark points more accurately. First is facial landmarks detection. Our model is based on the movement information of facial landmarks, so we need to detect the facial landmarks for each frame in the video. We use the 3DDFA-V2 algorithm [12] to obtain facial landmarks in 3D coordinates.

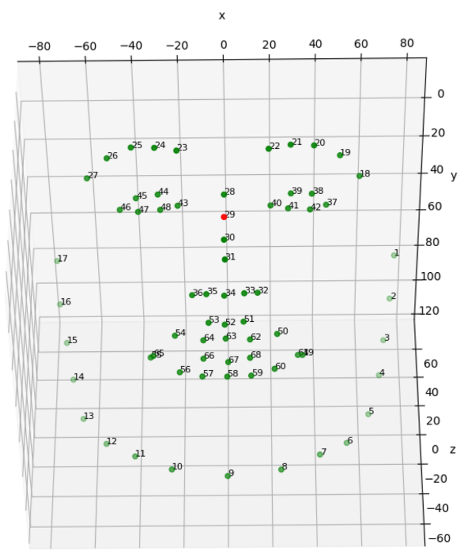


Figure 3: Facial landmarks with 3 coordinates extracted with 3DDFA-V2 algorithm

Second, we will standardize the landmarks data to make the position of each facial landmarks in each frame have the same position and looking direction, so that we can analyze the movement of each landmark point when the person is talking and interacting during the video.

We take point 29 (nasal root) as a root point for each frame, then we translate entire facial landmarks to make point 29 has coordinates (0, 0, 0). After this computation all facial landmarks in each frame will have the same root position.

To make sure the facial landmarks in each frame have the same looking direction, we make a line from point 29 to point 28 and rotate whole points around X axis to make the line coincides with the Z axis (90 degree). To do this, we project point 28 into surface ZY and calculate the angle between the 90-degree line and point 28.

$$angle = 90 - \arctan(p28z, p28y). \tag{1}$$

Then, we rotate all landmark points around X axis with the same angle with the rotation matrix formula [13]

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}. \tag{2}$$

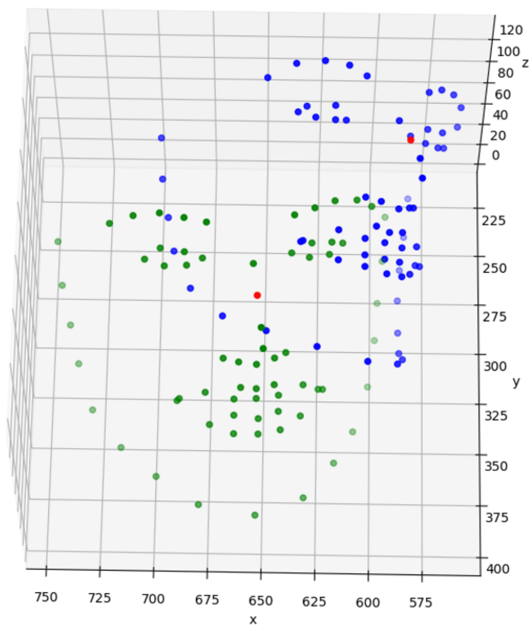


Figure 4: Facial landmarks of a person in two different frames

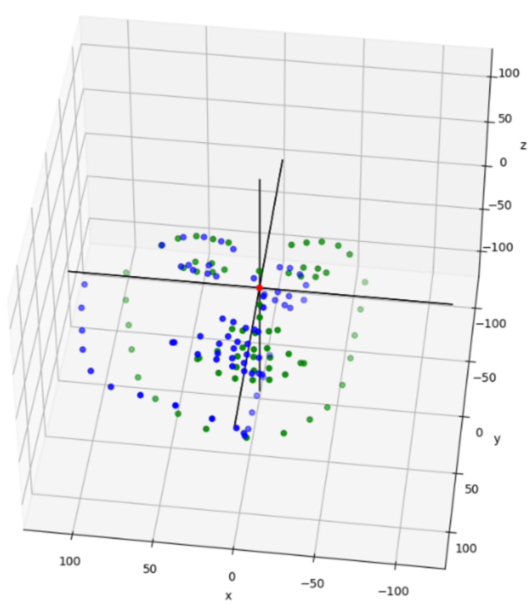


Figure 5: Facial landmarks of a person in two different frames

We make another line between eyes from point 40 to point 43 and rotate whole points around Z axis to make the line parallel with X axis. To do this, we project the line 40-43 on surface XY and find point projection from origin (0, 0) to the line 40-43. Finally, we calculate the angle between the 90-degree line and point projection.

$$angle = 90 - \arctan(pprojectionz, pprojectiony). \tag{3}$$

Then, we rotate all landmark points around Z axis with the same angle with the rotation matrix formula [13]

$$\begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{4}$$

When the standardization is finished, the facial landmarks in each frame now have the same root, same looking direction. So, we can analyze how the points in the face change when someone is talking.

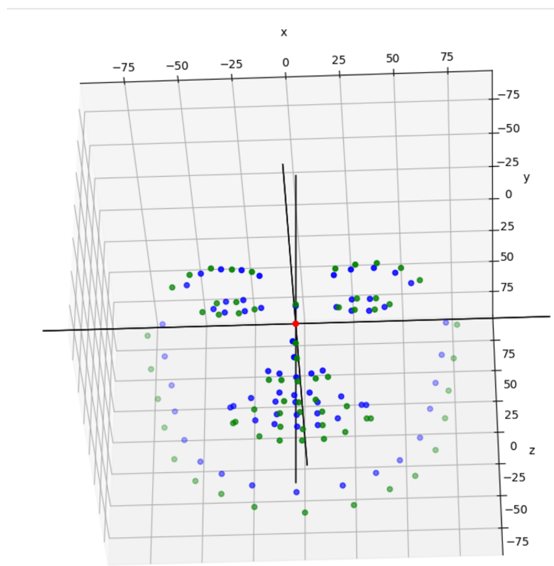


Figure 6: Result after standardizing the facial landmarks

Third is compute feature values. Once the standardization step has been completed, we can move on to the next phase of the process. For each dimension of each point, we compute Mean and Standard Deviation values in all frames. Within each video of each person, we have 68 (landmarks), 3 dimensions, 2 computation values, so in total we have 68*3*2=408 features data. This step allows us to gain a better understanding of the data and to identify any patterns or trends that may be present.

Predict Big Five scores

We use UDIVA dataset [14] and dataset we surveyed ourselves to train the CNN-LSTM model, which learns to identify patterns and relationships between different aspects of the videos and the personality scores. The hybrid CNN – LSTM is the combination of strengths of convolutional neural networks (CNN) and long short-term memory (LSTM). CNN can extract features from data while LSTM can preserve long-term dependencies, this lets us reduce data dimensions, gain valuable information and learn moving patterns from frames extracted from interview video. We also compare LSTM several regression algorithms. We also train these datasets with ResNet model, abbreviated from Residual Neural Network model. It is a Convolutional Neural Network (CNN) architecture designed to support hundreds or thousands of convolutional layers. ResNet stacks multiple identity mappings (convolutional layers that do nothing at first), skips those layers, and reuses the activations of the previous layer. Skipping speeds up initial training by compressing the network into fewer layers. Furthermore, we train these datasets with VGG19, VGG19 is a convolutional neural network that is 19 layers deep. VGG19 is an advanced CNN with pre-trained layers and a thorough comprehension of the characteristics of shape, color, and structure that define an image. VGG19 is very deep and has been trained on millions of diverse images with complex classification tasks. Once the model has been trained, we can use it to predict the Big Five scores for latest videos, allowing us to gain valuable insights into the personality traits of the individuals in the videos. Overall, our approach is a tool for understanding and predicting human personality.

3.3. Big Five proposal formula

After obtaining the Big Five questionnaire response score dataset, we proceeded to calculate each person's 5 personality scores based on their answers in the survey. We have researched and used the formula below to calculate the Big Five personality score.

$$P_i = \alpha + \sum_{j=0}^{positive} p_{i_j} - \sum_{k=0}^{negative} p_{i_k}, \tag{5}$$

$$P_{i\_scaler} = scaler(P_i; min; max). \tag{6}$$

The formula includes each step of the calculation as follows:

- With P_i is the score of each calculation method in the Big Five model, which is calculated by taking the constant alpha of each personality plus the total number of answer points of positive questions and then subtracting the total number of answer points for each personality negative questions. For each calculation, the number of P_i points will be between 0 and 40 points.

-Then, based on the minimum - maximum value from the score of each personality calculated in the Visual Model process, use MinMaxScaler() of the Scikit-learn (Sklearn) library - a library of machine learning algorithms, widely used in the scientific Python community and supports many machine learning application areas [15], to normalize the calculated P_i score to bring back the P_{i_scaler} score that matches the score of the personality point calculation through Visual Model one by one.

- After calculating the score of each personality in the Big Five model from the Visual Model and Big Five Proposal Formula process, we researched and synthesized the result according to the formula below.

$$P_{i\_result} = \frac{P_{i\_scaler} + P_{i\_CV}}{2}, \tag{7}$$

$$E_{i\_Best} = \min \sum_{m=0}^{N} P_{i\_scaler;m} - P_{i\_CV;m}, \tag{8}$$

$$P_{i\_result\_inverse} = scaler\_inverse(P_{iresult}). \tag{9}$$

The formula includes the following steps:

- First, perform averaging the scores from the Big Five survey that have been normalized P_{i_scaler} and the score through Visual Model processing P_{i_CV} to return the combined result P_{i_result}.

- In calculating the P_{i_result}, if the difference between the two scores is too large, the E_{i_Best} coefficient will be used to adjust the two values to be as close to each other and to have as minor difference as possible to ensure high accuracy.

- After calculating the P_{i_result}, the results will be inversed to bring the score of each personality back to the BFI scale and return the result $P_{i\_result\_inverse}$ of each personality in the Big Five model.

After getting the final Big Five results, we drew the Big Five Chart and made comments, and evaluated that person based on the 5 characteristics of the Big Five model. With the Big Five Chart plotting, we used the radar graph to show the 5 personality traits of the person on the graph with the Big Five results as input and the graph results show the score of each personality corresponding to each vertex in the graph. Using radar graphs to stand for Big Five results helps people see whether they tend to be positive or negative with each personality in the Big Five model. Next, we researched and collected data on the evaluations and comments of each Big Five personality from related survey sites. After collecting, we analyzed the data based on aspects of each personality in the Big Five model to make a specific assessment. We then divided each assessment into different score ranges to give a visual assessment, consistent with the Big Five results.

4. EXPERIMENTS

4.1. Dataset preparation

We have combined the dataset between a UDIVA dataset (a publicly available dataset) and a dataset we surveyed ourselves to train the model is more suitable for Asian facial features To get the data set for calculating the score of each personality in the Big Five model, we conducted a Big Five survey with more than 100 volunteers. The Big Five survey was conducted by recording a video interview of each volunteer (needed to open the cam with the mic and receive the volunteer's consent) asking about themselves and the set of 50 Big Five questions. The interview is conducted through an online meeting, and the interviewees will in turn introduce themselves and answer the Big Five questionnaire. The interview process uses Vietnamese. Before the interview, volunteers will be informed about self-introduction questions and how to answer questions in the survey form. The surveyor will read the question and the volunteer will answer on a scale from 1 to 5 standing for the level from most disagree to most agree (1: completely disagree, 2: disagree, 3: neutral, 4: agree, 5: completely agree). The interview takes place on a video lasting about 5 to 10 minutes. The volunteers are young people between 18 and 30 years old. After finishing the Big Five survey, the results obtained were a dataset of 105 people including an mp4 file containing the interview video and a txt file containing the results of answering the Big Five questionnaire.

We use the UDIVA dataset to train our model. The UDIVA dataset is composed of 90.5h of recordings of dyadic interactions between 147 voluntary participants (55.1% male) from 4 to 84 years old (mean=31.29), coming from 22 countries (68% from Spain). Recordings take place in 5 different interaction contexts: talk, animals game, lego building, ghost blitz, gaze events. The structure of dataset split into train, validation, test data folder. Videos of all contexts are used to train our models; each video will be extracted 700 frames to detect 3d facial landmarks and calculate features. In total, after Feature Extraction process, each video will obtain 68 (landmarks) $\times$ 3 (dimensions) $\times$ 2 (feature value) = 408 features data. To make the data compatible with CNN-LSTM, VGG19 and ResNet model, we reshape features data into 27×14 dimensions.

4.2. Evaluation metrics

For accuracy measuring, we use MSE [16] metrics to evaluate our models. This metrics take average squared between the estimated value and the actual value, so that it helps us to know how far between the predicted value of the model and the actual value.

4.3. Experimental results

Big Five personality survey

We use train, validation, test data of UDIVA for training and evaluating models with several algorithms contains Random Forest Regression [17], Linear Regression [18], CatBoost Regressor [19], LSTM [20], hybrid CNN-LSTM, VGG19, ResNet [21].

Table 1: Comparison of the results of each algorithm. The value on the table is MSE value, a lower number shows the better accuracy.

Personality Traits	LN	CTB	LSTM	RFR	CNN-LSTM	VGG19	ResNet
Openness	2.1928	1.3106	1.1141	1.1388	0.8862	0.8785	0.9542
Conscientiousness	1.7966	0.6288	0.6906	0.6136	0.6447	0.6174	0.6354
Extroversion	1.8925	0.9926	1.1803	1.2534	1.2308	1.2160	0.9437
Agreeableness	1.8925	0.9926	1.0105	0.9734	0.9699	0.9450	0.9638
Neuroticism	2.0273	1.3770	1.3779	1.3472	1.2541	1.2410	1.2115
Average	1.9244	1.1280	1.0747	1.0653	0.9965	0.9796	0.9417

Table 1 shows that the hybrid ResNet model has the best accuracy of all algorithms, so we decided to use this model to predict Big Five scores for interview video. The predicted Big Five scores of visual models will be combined with Big Five model results, by calculating mean value for each Big Five index.

The performance of a CNN-LSTM, ResNet and VGG19 model trained on UDIVA would likely be evaluated based on its ability to accurately capture and analyze facial expressions and movements associated with different personality traits.

After the end of the experiment, the obtained results include the score of each personality in the Big Five model of each participating volunteer along with an assessment and comment on that person's personality based on the score achieved. yes, and a radar graph showing their 5 traits is either positive or negative.

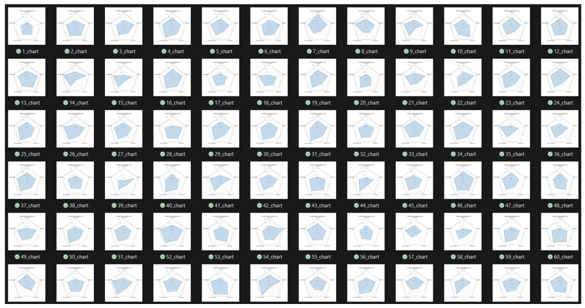
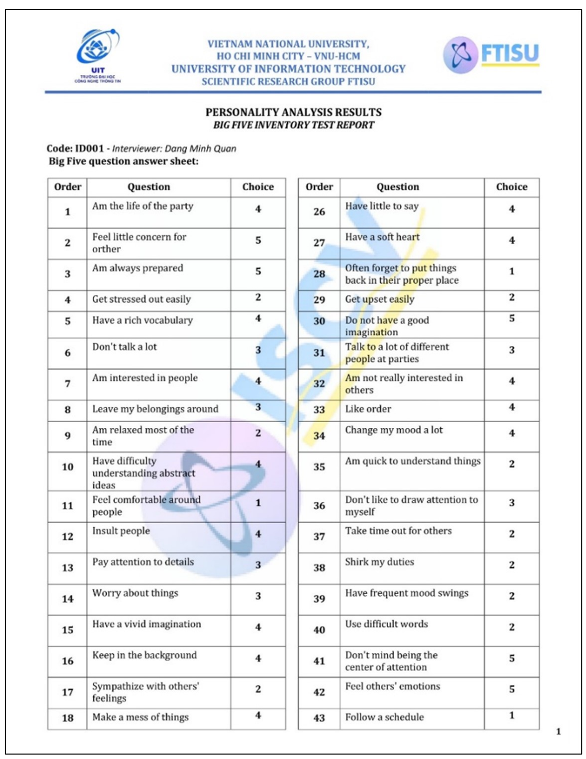


Figure 7: Big Five results visualize by using radar graph

All experimental results were processed, compiled into a PDF report file, and sent to the volunteers who took in the Big Five survey. This Big Five report file was specially designed by us for the survey participants. The report includes the participants' information, the score for each question, the total score of each personality along with comments and a graph showing the 5 characteristics of the Big Five model.



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PERSONALITY ANALYSIS RESULTS
BIG FIVE INVENTORY TEST REPORT

Code: ID001 - *Interviewer: Dang Minh Quan*
Big Five question answer sheet:

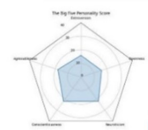
Order	Question	Choice	Order	Question	Choice
1	Am the life of the party	4	26	Have little to say	4
2	Feel little concern for orther	5	27	Have a soft heart	4
3	Am always prepared	5	28	Often forget to put things back in their proper place	1
4	Get stressed out easily	2	29	Get upset easily	2
5	Have a rich vocabulary	4	30	Do not have a good imagination	5
6	Don't talk a lot	3	31	Talk to a lot of different people at parties	3
7	Am interested in people	4	32	Am not really interested in others	4
8	Leave my belongings around	3	33	Like order	4
9	Am relaxed most of the time	2	34	Change my mood a lot	4
10	Have difficulty understanding abstract ideas	4	35	Am quick to understand things	2
11	Feel comfortable around people	1	36	Don't like to draw attention to myself	3
12	Insult people	4	37	Take time out for others	2
13	Pay attention to details	3	38	Shirk my duties	2
14	Worry about things	3	39	Have frequent mood swings	2
15	Have a vivid imagination	4	40	Use difficult words	2
16	Keep in the background	4	41	Don't mind being the center of attention	5
17	Sympathize with others' feelings	2	42	Feel others' emotions	5
18	Make a mess of things	4	43	Follow a schedule	1

1

Figure 8: Big Five report - page 1

19	Seldom feel blue	2	44	Seldom feel blue	2
20	Am not interested in abstract ideas	5	45	Am not interested in abstract ideas	5
21	Start conversations	2	46	Start conversations	5
22	Am not interested in other people's problems	5	47	Am not interested in other people's problems	5
23	Get chores done right away	4	48	Get chores done right away	1
24	Am easily disturbed	3	49	Am easily disturbed	2
25	Often feel blue	2	50	Often feel blue	3

Results of your personality:



Your score	
Openness	16/40
Conscientiousness	22/40
Extroversion	16/40
Agreeableness	18/40
Neuroticism	22/40

Conclude:

Extroversion: You have a relatively low extroversion. You have an introverted personality and like to be independent. You may feel more comfortable being alone and not needing to share as much with others. You don't like fast and snappy conversations that can make you feel forced and uncomfortable. You often want more time to think and form your opinion. You don't like being the center of attention, this job can make you feel uncomfortable and uncomfortable. You usually want to keep your distance and don't want to stand out from the crowd.

Conscientiousness: You have a relatively high degree of self-control. You take the time to prepare and plan your work which helps you to minimize errors by carefully preparing before undertaking a task. At the same time you enjoy having A clear schedule helps you to manage your time effectively and make progress in work and life.You pay attention to the details of your work, which helps you to ensure that the work is done correctly. and complete. And you can spot defects and fix them before they become a big problem.

Openness: You have a relatively low open-mindedness. You may have difficulty imagining and generating new ideas. You have no particular interest in the arts and do not make time for activities related to the arts. You are not interested in discovering new experiences and tend to stay away from experiences beyond your comfort and safety.You are not motivated to learn and discover new knowledge. Sometimes you don't like abstract concepts or theories.

Agreeableness: You have a relatively low sociability. You care less about others, don't care about other people's feelings, and care less about other people's problems. This makes it impossible for you to understand the people around you and create better relationships.

Neuroticism: You have a relatively high sensitivity. You go through a lot of stress, worry about many things, get upset easily. This can make you easily distracted and unable to focus on a particular task for long periods of time. From there you may feel tired and lack energy to face life's challenges.

2

Figure 9: Big Five report - page 2

5. CONCLUSION AND FUTURE WORKS

Many individuals are always interested in analyzing and identifying someone's reasoning and behavior only based on the morphological and sociological numbers on their face. It is crucial and helpful to apply the Big Five model in study to evaluate many sides of a person's personality. After the end of the experiment, the obtained results include the score of each personality in the Big Five model of each participating volunteer along with an assessment and comment on that person's personality based on the score achieved, and a radar graph showing their 5 traits is either positive or negative. All experimental results were processed, compiled into a PDF report file, and sent to the volunteers who participated in the Big Five survey. This Big Five report file was specially designed by us for the survey participants. The report includes the participants' information, the score for each question, the total score of each personality along with comments and a graph showing the 5 characteristics of the Big Five model.

We also trained the model from the UDIVA dataset to train the model, then we conducted a survey of more than 100 volunteers who were interviewed via online form to predict the outcome. unique Big Five numbers. During the analysis, we used the 3DDFA-V2 algorithm. We then use the 3DDFA-V2 algorithm to estimate the 3D shape and pose of a face from 2D images or videos. The reason we do this is to accurately analyze and generate 3D face models. We then use this dataset to train the LSTM model, which learns to identify patterns and relationships between different aspects of the videos and the personality scores. Once the model has been trained, we can use it to predict the Big Five scores for new videos, allowing us to gain valuable insights into the personality traits of the individuals in the videos.

In the future, we plan to explore and employ new algorithms to enhance the accuracy of our model. Along with LSTM and UDDFA-V2 algorithms, we could combine new mathematical techniques with older algorithms to achieve optimal results or replace other algorithms. Additionally, we will expand our data collection efforts by interviewing individuals from various age groups and occupations. Currently, our team primarily interviews information technology students but we aim to diversify our pool of interviewees to yield more comprehensive data. We plan to create more detailed and thought-provoking questions that will help us better understand the interviewee's personality. Instead of limiting ourselves to 50 questions, we will create more questionnaires that are tailored to the interviewee's personality. Through these methodical developments, we are confident that we will be able to increase the accuracy of our model and make it increasingly realistic.

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