Asynchronous Interview Analysis

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Abstract:- Conventional interviewing procedures often lack to grasp a deep understanding of their interviewees. Interviewers could fail to observe important facial features, textual tone, and body language during the interview process. The proposed system provides a thorough approach to understand how the interviewee behaves and feels during the interviewing process. A significant feature of this system is the ability to measure and quantify the big 5 traits of personality with the help of machine learning and natural language processing. Additionally, this paper presents how the amalgamation of various algorithms and approaches can help in determining the overall personality of the interviewee.

Keywords:- *Natural Language Processing, Machine Learn- ing, Artificial Intelligence, Sentiment Analysis, FastAI.*

I. INTRODUCTION

Sentiment Analysis is the process of determining whether a piece of writing is positive, negative or neutral. It is an essential component for understanding a person's emotions. Using such analysis as an automated system in an interview environment can reveal critical information about the person's behavior. There's also the assurance that the system will not show bias towards a person. Additionally, it can also detect many features that can be overlooked by a human. However, judging a person only based on their intellect is not sufficient. Only a complete thorough analysis, can give us what the person is thinking vs. what the person wants us to believe.

For this complete analysis, our system will be integrating 3 essential measurement traits. The first one determining the aptitude of a person. This aptitude will be measured using a basic knowledge test where the person will be asked questions on his applied position. This will be followed by a psychometric test which involves OCEAN analysis.

The second step involves, determining their thought process using a writing test. This can help employers determine whether the student's thought process is positive, negative or neutral.

The final step involves an asynchronous face-to-face inter- view. This interview will be recorded to understand how the interviewee reacts to specific questions and how he/she feels throughout the interview process.

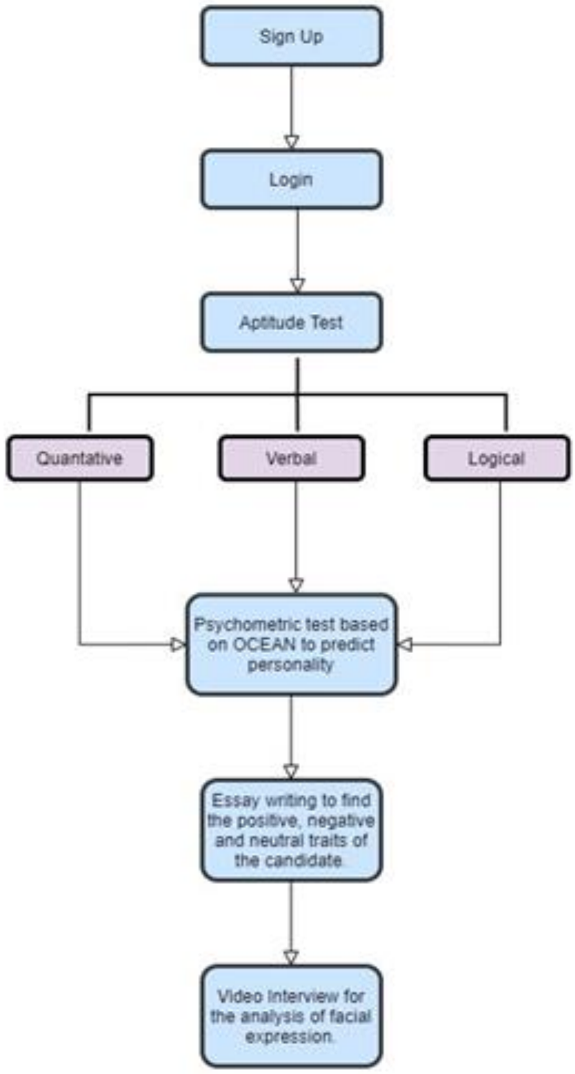

Fig 1:- System Flowchart

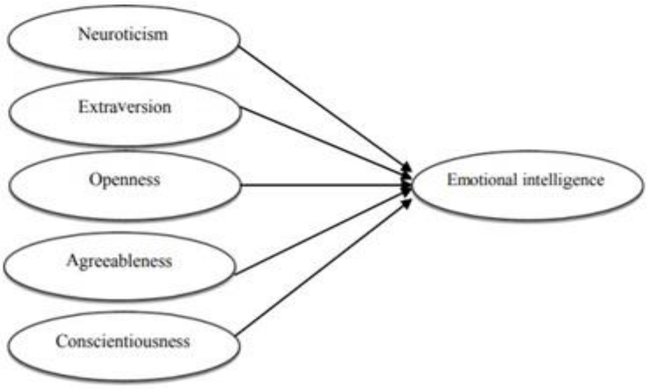

Fig 2:- Big Five Traits

II. LITERATURE REVIEW

A. Personality Prediction

- predicts personality using OCEAN analysis for hand- writing. However, this approach has 2 major drawbacks. Firstly, a major aspect of handwriting analysis is that it predicts accurate personality only if handwriting sample is written in a relaxed mood. [1] does not consider that. Secondly The online tools used for automatic personality assessment using handwriting analysis requires basic knowledge of various writing features. The person with this knowledge can use these tools efficiently and effectively. However, a layman cannot use these tools for his/her benefit. There are possibilities of human errors incorrectly matching writing to the given sample. Hence, the accuracy of the results will be compromised.

B. Facial Expression Detection

- uses Mini Xception which is inspired by Xception
- model, This architecture combines the use of residual modules and depth-wise separable convolutions whereas we use deep residual network [4] resnet50. The system proposed in [2] achieved an accuracy of 66% on 7 class "angry", "disgust", "fear", "happy", "sad", "surprise", "neutral". The major drawback is that the data-set used i.e. Fer2013 has many mislabelled images and the distribution of images is not equal in each class. Class with less image is often predicted wrong. To overcome this we cleaned the Fer2013 data-set and eliminated the class which was not required.

III. METHODOLOGY

❖ *Aptitude And Personality Prediction*

For the first step, our system begins with general aptitude questions based on Quants, Verbal, Logical reasoning each consisting of 5 questions, continuing to psychometric analysis. In the psychometric analysis, our system determines the per- sonality by using OCEAN analysis. The Big Five personality traits, also known as the five-factor model (FFM) and the OCEAN model, is a taxonomy, or grouping, for personality traits. The big five traits are Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism.

A. Openness

Openness to experience (inventive/curious vs. consis- tent/cautious).

Openness is one of the factors which is used to describe a person's personality in the (FFM) Five-Factor Model. Open- ness includes six dimensions that are sensitivity, imagination, inner feelings, intellectual curiosity, and variety. In-depth psychometric research has indicated that these dimensions or qualities are significantly correlated. Thus, openness can be seen as a global personality trait comprises of a set of specific traits, habits, and proclivity that cluster together.

The type of questions ask are
1.Do you believe there is no absolute right and wrong?
2.Do you prefer to stick with things you know?

B. Conscientiousness

Conscientiousness (efficient/organized vs. easy- going/careless)

Conscientiousness is the persona trait of being careful, or diligent. Conscientiousness implies a preference to do a challenge well and to take responsibilities to others seriously. Conscientious people tend to be efficient and organized in preference to easy-going and disorderly. They showcase a tendency to reveal self-discipline, act dutifully, and aim for achievement; they show planned rather than spontaneous be- havior, and they're typically dependable. It is manifested in feature behaviors consisting of being neat, and systematic; also which include such elements as carefulness, thoroughness, and deliberation.

The type of questions ask are
1. Do you complete tasks successfully every time? 2.Are you always prepared?

C. Extraversion

Extraversion (outgoing/energetic vs. solitary/reserved).

The traits of extraversion (or extroversion) and introversion are a central measurement in a few human personality theories. The terms introversion and extraversion have been popularized through Carl Jung, although both the famous understanding and psychological utilization vary from his authentic intent. Extraversion tends to be manifested in outgoing, talkative, lively behavior, while introversion is manifested in greater reserved and solitary behavior. Rather than that specialize in interpersonal behavior, however, Jung described introversion as an "attitude-type characterized by orientation in life via subjective psychic contents", and extraversion as "an attitude- type characterized through awareness of interest on the exter- nal object."

The type of questions ask are 1.Do you make friends easily?
2. Do you feel comfortable around people?

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D. Agreeableness

Agreeableness (friendly/compassionate vs. challenging/detached).

Agreeableness is a character attribute indicating itself in a person's behavioral traits which might be perceived as sympathetic, kind, cooperative, understanding, and tender. In modern-day character psychology, agreeableness is one of the five essential dimensions of personality structure, reflecting man or woman variations in cooperation and social harmony. People who are rating excessive on this are empathetic and altruistic, even as a low agreeableness rating pertains to selfish behavior and a lack of empathy. The type of questions ask are 1.Do you like to help the needy?
2.Do you like to boast about your virtues?

E. Neuroticism

Neuroticism is one of the Big Five higher-order personality traits in the field of psychology. Individuals who score high on neuroticism are much more likely to be moody and to experience not so positive emotions such as anxiety, worry, fear, frustration, envy, jealousy, guilt, and loneliness. Neurotic people respond worse to stressors and are more likely to inter- pret everyday conditions as threatening and minor frustrations as hopelessly difficult. They are regularly self-conscious and shy, and they'll have hassle controlling urges and delaying gratification.

The type of questions ask are
1.Are you easily bothered by things? 2.Do you lose your composure easily?

All of the above traits were given a score on a scale of 1-9. The person attempting the test is given a set of questions. By answering the most appropriate answer score for the particular personality trait is increased by 1. If not answered with the most suitable option then scores are given accordingly i.e. 0.75, 0.50 and 0. 25. After answering all the questions of each trait we classify the person personality using linear regression into one of the five classes Extraverted, Serious, Responsible, Lively, Dependable. The data-set consists of 710 training samples and 316 test samples with attributes like gender, age, Openness, conscientiousness, extraversion, agreeableness, neuroticism.

❖ *Text Polarity*

In the second step of our system, we give the test taker a general topic like "Describe the best day of your life" or something on a similar line. The essay written by the test taker is analyzed for the sentiment. The result of the sentiment analysis would suggest the mindset of the person whether he/she has a positive, negative or neutral opinion towards life. To achieve this we use TextBlob. TextBlob is a built-in python library and offers simple access to its methods and perform basic Natural language processing functions. The sentiment function of TextBlob returns two attributes, subjectivity, and polarity. Polarity lies in the range of [-1,1] where 1 means the given statements are positive and -1 means the given statement is negative. Subjective sentences often refer to personal opinion, emotion or judgment whereas objective often refers to factual information. Subjectivity also lies in the range of [0,1].

let's see an example:

```
from textblob import TextBlob
TextBlob("not great at english").sentiment
```

```
Sentiment(polarity=-0.2, subjectivity=0.375)
```

This tells us that the English phrase "not great at English" has a polarity of about -0.2, meaning it is slightly negative, and subjectivity of about 0.375, meaning it is fairly objective.

```
Each word in the lexicon has scores for:
1)     polarity: negative vs. positive    (-1.0 => +1.0)
2) subjectivity: objective vs. subjective (+0.0 => +1.0)
3)    intensity: modifies next word?      (x0.5 => x2.0)
```

The wordbook it refers to is in en-sentiment.xml it is an XML document that includes four entries for the word "great".

In addition to the polarity, subjectivity, and intensity of the phrase there's also "confidence". In the case of "great" it's all the same part of speech (JJ, adjective), and the senses are themselves natural language and not used.

To simplify for readability:

word	polarity	subjectivity	intensity
great	1.0	1.0	1.0
great	1.0	1.0	1.0
great	0.4	0.2	1.0
great	0.8	0.8	1.0

When calculating sentiment for a single word, TextBlob uses a sophisticated approach recognized to mathematicians as "averaging"

```
from textblob import TextBlob
TextBlob("good").sentiment
```

```
Sentiment(polarity=0.7, subjectivity=0.6000000000000
```

The polarity is multiplied by -0.5 when negation is used and it does not affect subjectivity.

```
from textblob import TextBlob
TextBlob("not good").sentiment
```

```
Sentiment(polarity=-0.35, subjectivity=0.6000000000000001)
```

Recognizing "very" as a modifier word, TextBlob will ignore polarity and subjectivity and simply use intensity to modify the following word:

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word	polarity	subjectivity	intensity
very	0.2	0.3	1.3

```
from textblob import TextBlob
TextBlob("very good").sentiment
```

```
Sentiment(polarity=0.9099999999999999, subjectivity=0.780000(
```

The polarity gets maxed out at 1.0, but you may see that subjectivity is also changed by "very" to turn out to be 0.6*1.3
= 0.78

❖ *Facial Expression Detection During Interview*

Finally, in the third step, we have used Resnet50 to detect the certain facial expression of the person/interviewee without any biases. Fer2013 was utilized to train this CNN model with the following classes [0: angry, 1: happy, 2: sad, 3: surprise, 4: neutral]

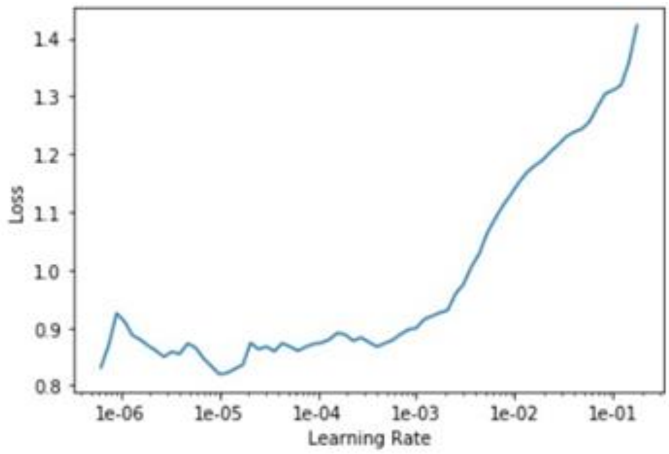

Fig 3:- Learning Rate

ResNet-50 is a deep residual network. The "50" refers to the range of layers it has. It's a subclass of convolutional neural networks. The most important innovation of ResNet is the skip connection. As you know, without adjustments, deep networks regularly are afflicted by vanishing gradients, i.e. as the model backpropagates, the gradient gets smaller and smaller.

The architecture of ResNet50 has four levels as shown in the diagram. Every ResNet structure performs the initial convolution and max-pooling by using 7×7 and 3×3 kernel sizes respectively. Afterward, level 1 of the network begins and it has 3 Residual blocks containing three layers each. The size of kernels used to carry out the convolution operation in all 3 layers of the block of level 1 is 64, 64 and 128 respectively. As we progress from one level to another, the channel width is doubled and the dimensions of the input are reduced to half. For deeper networks like ResNet50, ResNet152, etc, bottle- neck style is employed. For every residual function F, three layers are stacked one over the other. The three layers are 1×1, 3×3, 1×1 convolutions. The 1×1 convolution layers are accountable for lowering and then restoring the dimensions. The 3×3 layer is used as a bottleneck with smaller input/output dimensions. Finally, the network has an Average Pooling layer followed by a completely linked layer having a thousand neurons.

ResNet50
Input layer
Convolutional layer (7x7)
3x3 MaxPooling
[1x1, 64; 3x3, 64; 1x1, 256] x3
[1x1, 128; 3x3, 128; 1x1, 512] x4
[1x1, 256; 3x3, 256; 1x1, 1024] x6
[1x1, 512; 3x3, 512; 1x1, 2048] x3
AveragePooling
Output (sigmoid neuron)

Fig 4:- ResNet50 Architecture

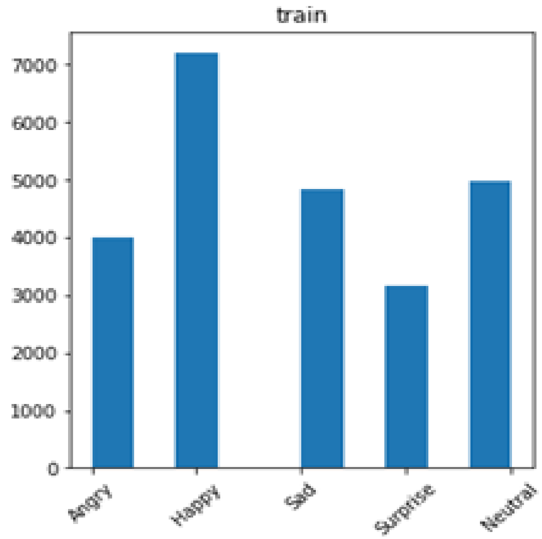

Fig 5:- Distribution of training data

The model achieved an accuracy of 75% with the help of 24176 (Training) + 3037 (Public Test) + 3006 (Private Test)
= 30219 images.

The loss obtained was 0.649742. This model was then fed with real-time images of the interviewee. The interviewee had to respond to the questions displayed. The candidate's reaction was then captured. These real-time images were cropped using HAARCASCADE [5] to extract the face of the interviewee and then resized to 48X48 pixels. These were fed to the neural network. Based on how the interviewee is reacting, the model uses facial features to identify the individual's sentiment. The parameters are happy, sad, neutral, surprised and angry. The model logs these expressions in each frame in a text file. Then this text file is analyzed and detects the amount of time the individual was showing those expressions. Based on the percentage of the parameters, the overall facial expression of the individual is calculated.

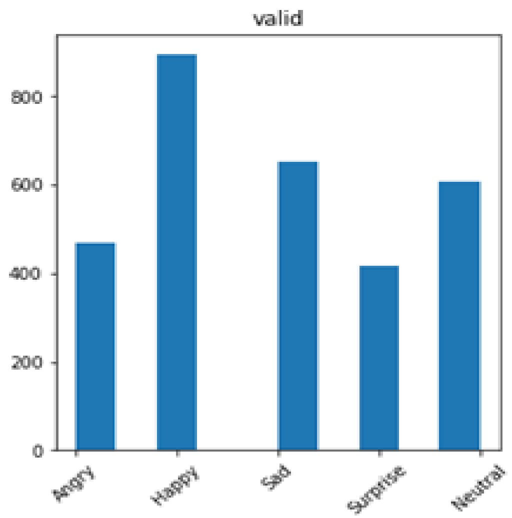

Fig 6:- Distribution of validation data

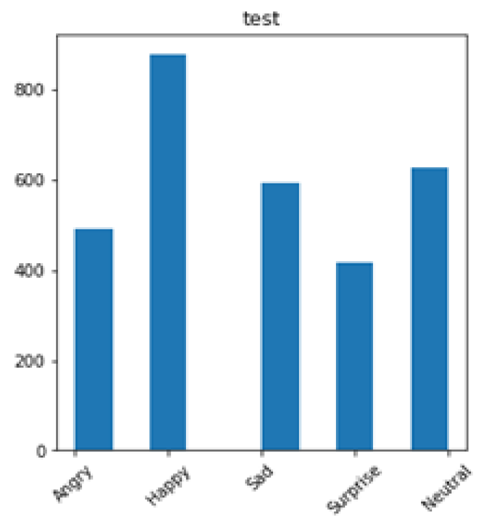

Fig 7:- Distribution of testing data

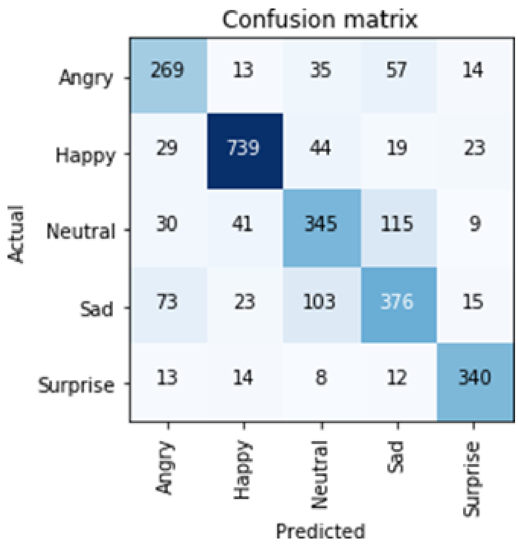

Fig 8:- Confusion Matrix

IV. RESULTS

A. Personality Prediction

The accuracy of the model for predicting personality achieved 80% using logistic regression.

B. Facial Expression Detection During Interview

The facial Expression detection model achieved an accuracy of 75% After analyzing the top losses shown below, we found out the forced facial features were classified with low confidence. Other facial features like in image number 7 of the top losses were difficult to classify as the capture features of 2 or more classes. To conclude, the model performs reliably in an interviewing environment where a single feature class will exist.

Fig 9:- Toploss

C. Text Polarity

The Accuracy of Text polarity i.e. finding sentiment using TextBlob is 60.5%

V. CONCLUSION

The comprehensive system presented above helps interview- ers to understand their interviewees better. This system doesn't aim to replace the interviewer but to aid them in their process. Further, it helps to gain important insights and details that the interviewers could have missed. This thorough procedure can be used in a practical environment to improve the overall evaluation process of a candidate. Hence, this research aims at helping companies with recruitment policies and it makes their recruitment process efficient by filtering out candidates according to their requirements.

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