

Automatic Personality Recognition In Interviews Using Convolution Neural Network (CNN)

Ramya k¹ and Sheba Selvam ²

MTech Student¹, B.N.M Institute of Technology, Bangalore, India

Associate Professor², B.N.M Institute of Technology, Bangalore, India

ABSTRACT

Since the development of artificial intelligence, human-computer interaction, persona computing, and psychological testing have all benefited from the automated character assessment of video conversations to find personality traits. Deep learning (DL) techniques have enabled advancements in system cognition and creative and prescient abilities. Researchers have been able to recognise nonverbal cues and personality traits are attributes to them thanks to the creation of CNN (convolutional neural network) models capable of recreating human looks reliably via means of a camera. An entire AI system was used in this investigation. The video interviewing system and asynchronous video interview (AVI) processing were used to create the interviewing tool. Based only on the collected attributes, the Tensor Flow AI engine will robotically create personas (APR). Genuine personality ratings from facial expressions and self-reported surveys have been computed using the AVIs and real personality rankings from the AVIs. The studies' findings demonstrate that our AI-based interview bot is capable of accurately identifying an interviewee's "personality" traits. Our research also demonstrates that the semi-supervised deep learning technique surprise good performance in terms of despite the absence, automatic personality recognition of time-consuming manual labelling and annotating. This was true even in the absence of large-scale data. The Intelligence interview agent can be deployed in addition to or in substitute of current self-reported personality evaluation techniques, which job hopefuls can also manipulate to produce socially acceptable outcomes.

KEYWORDS Convolution neural network (CNN), automatic personality recognition, online interview, Image pre-processing, facial expression, emotion detection.

1. INTRODUCTION

Although major advancements in HCI, or human-computer interaction, and ongoing efforts to enhance the user experience with computer systems, it has long been understood that agents must be able to detect and respond to users' affective states. Despite being crucial to human behaviour, affect is a highly individualised phenomena that is influenced by a wide range of environmental and psychological variables, including personality [1]. The database enables multimodal research on human affective reactions using neurophysiological signals, as well as their relationships to personality, mood, social environment, and stimulus duration. Two separate experimental settings are used to collect the data. In the first, 16 brief emotional videos were viewed by 40 people. They viewed four lengthy videos in the second, some of which were produced by themselves and others by businesses [2]. The perception of personalities is influenced by a variety of subjective factors, including culture, society, context, look and masculinity. Methods for automatic persona perception are intended to anticipate how the target will be perceived, not the target's genuine personality. They must deal with human bias as a result, which is unavoidably transmitted to the practise data. Contrarily, prejudice evaluation computing personality is a field that is still developing [3]. Excessive psychological stress, lengthy work hours, and increased labour intensity can fatigue people and impair their cognition and motor function. Excessive weariness

and physical injury can be avoided by detecting an individual's fatigue status [4]. Due to its subjective nature, pain is a difficult thing to quantify. A person's ability to identify and report a pain episode is a key component of most contemporary pain assessment techniques. Contrarily, a multitude of factors, including personality traits and physical and mental health, have an impact on how people perceive and express pain [5]. Automated content analysis to define people's behavior has grown in popularity, with applications in affective computing, individual's developmental, To mention a few, there is gambling, privacy, advertising, and health [6]. Computer vision relies heavily on visible psychology and mood analysis. Existing works address them one by one. In this study, we look into whether Such complex affective characteristics and their relationships could be learnt in the wild from face photos [7]. Numerous fields, including psychology, neuropsychology, and signal processing have conducted substantial research on personality analysis. In recent years, it has also grown in popularity as a study subject for visual computing. From a computational perspective, speech and text have been by far the most taken into account signals of information for assessing personality [8]. A Deep Neural Networks-based model for predicting perceived personality is presented in this paper. It can measure Using the Five-Factor approach, personality traits are extracted from a portrait image (Big Five)[9]. Decision support tools should be able to explain and analyse their findings. Despite their importance, academics have only recently started to examine these factors [10]. This study aims to address two significant issues that current automatic personality analysis systems encounter frequently: 1. Using very brief To infer character traits rather than long-term behaviour, use video clips or even single frames; 2 Lack of methods to encrypt individual face dynamics for character identification [11]. A mobile or wearable device user's motion activities are particular to that user, therefore using individualised motion activity examples can improve the precision of motion activity context detection. It is not practical to collect individualised motion activity samples from device users. We describe a semi-supervised method in this research for creating a customised classifier from a pre-built generalised classifier in order to improve the accuracy in classifying a wearable or mobile device user's action activities. The difference is in selecting customised statistical samples using statistics-theoretical standards out of all the customised statistical samples that were collected from the target person[12]. Intelligent surveillance systems are often used in a number of important sectors, including airports, ATMs, and financial institutions, to ensure greater security and safety. Complex behaviour recognition systems are still in high demand. Traditional methods of spotting suspicious behaviour based on access to forbidden areas or suspected theft, fraud, or loitering are insufficient. These actions don't really qualify as a suspect list. Involuntary behaviours including face movements, facial features, and feeling components are being exploited in novel ways to extract behaviours. The complexity of intelligent algorithms and the shortcomings of existing methods serve as the driving forces behind this endeavour [13] Deep learning algorithms for still-to-video FR usually result in a low level of accuracy since faces in unconstrained videos are matched against a reference gallery that has a single facial picture for each participant. Recently, robustness to intra-class variations has been extended using pair-wise face matching with Deep Siamese networks. Even though neural networks can increase trendy accuracy, the lack of prior knowledge from the target domain necessitates the acquisition of an enormous number of images to accommodate for all possible capture scenarios[14]. We use user surveys, team evaluations of the main participant and discussion starter, and team judgements of the "Big Five" personality

traits to link these traits to these traits. We demonstrate that our algorithms, which might be incorporated into automatic group meeting comprehension systems, achieve a present-day Big-Five personality characteristic predicted accuracy of 80% on average [15]. A buddy referral system is a must for any social network system (FRS). As a result of the growth of social networking websites, numerous In recent years, FRSs have been proposed. The majority of them, meanwhile, use homophile-based systems. Relationship quality is the propensity to bond and associate with others who are similar to oneself. In other words, these systems will recommend buddies based on what you have in common with them. Homophile-When a character attribute, like age, race, or gender, locality, employment, or way of life, is the common attribute, based FRS is appropriate [16]. This research explores the relationship between facial characteristics and behavioural qualities. To agree the association between face features and personality traits, a face-based machine computational character qualities categorization is used. First, a database of face images and the corresponding scores for personality traits is created. Then, facial characteristics are determined using mechanically recognised facial landmarks. Second, the classifiers are able to categorise persona attributes entirely based on the face data extracted. The suggested approach is then used to determine the one-factor and two-factor groups of character qualities [17]. Researchers prefer using the Big Five features to automatically analyse personas. In tasks combining human-computer and robot interaction, personality identification is anticipated to have a bright future. A variety of information found in human speech can be exploited to pinpoint speaker characteristics. On the other hand, the main topic of our research is the rich content of nonverbal components in human speech [18]. This essay investigates the relationships between specific personality traits and contentment at work. The main goal of this study is to examine how personality traits like negative affectivity, openness to experience, and psychoticism affect job satisfaction and to emphasise the significance of character traits in determining an the degree of job pleasure of employees. Work happiness and the Big Five character qualities are among the factors. This study's primary goal is to show that there is no meaningful correlation between the following primary five factors and job happiness. The aforementioned elements would significantly affect job satisfaction. It was previously determined whether traits like neuroticism, extraversion, and psychoticism are connected to job satisfaction using correlation analysis [19]. Predicting an individual's personality is a difficult task in both organisations and everyday life. Personality prediction is based on a variety of elements, which may differ from one person to the next. Personality prediction is the process of determining an individual's personality based on their actions in various settings and observations of their behaviour in various scenarios. Personality traits are a set of qualities that people have depending on their ideas, feelings, and actions. Personality qualities can be both positive and detrimental [20]. Recent research in computer vision and intelligent video surveillance has focused heavily on the detection of suspicious actions. For surveillance systems that must stop crimes and treacherous acts in their tracks, action recognition approaches are very important. We introduce 3D-Convolutional Neural Networks (3D-CNN) with a 3D motion cuboid in this paper to detect and recognise actions in videos [21].

2. RELATED WORK

J. Wache, et al. are among the authors. [1] In light of prior findings, we examine the Before analysing the both linear and non-linear physiological correlates of emotion and personality, correlations between users' emotional and personality judgments should be considered. Our research demonstrates that non-linear statistics, as opposed to linear statistics, are better at capturing the relationship between emotion and personality. We're here at last. Try to identify binary emotions and personality traits using physiological markers. M. K. Abadi, et al. [2] The participants' frontal HD footage, RGB, and depth complete body movies were all captured. Participants' emotions were noted using both self-reports of external evaluations of valence and arousal and affective levels. C. Palmero, et al. and [3] We look into a number of possible biases that may affect how people perceive a person's personality, including beauty, age, gender, and ethnicity. We also look into how these factors may alter how well people can estimate the perceived personality. To do this, we outline a multi-modal deep neural network that mixes unprocessed visual and audio data with attribute-specific model predictions to regress apparent personality. Zhang and Wang, F. [4] A fatigue movement detection model primarily based on Support Vector Machines is created using a variety of characteristic parameter mixes in accordance with the admission and rejection criteria of the Sequential Forward Floating Selection (SFFS) algorithm (SVM). P. Thiam and other, [5] Experimental validation of the assessment based on the SenseEmotion Database demonstrates the efficacy of the multi-modal classification approach with classification quotes of 89.33 percent, 58.32 percent, and 42.36 percent in a 2-class, 3-class, and 4-class ache intensity classification task, respectively. X. Baró, et al., [6] Three personality traits—Psychoticism, Extraversion, and Neuroticism—are inferred using a Hidden Markov Model, which is fed the data. According to the authors, their accuracy rates L. Zhang, et al. [7] There is a dedicated dataset with annotations for emotion and persona networks. Additionally, a defeat resembling conflict feature is applied to improve illustration consistency across different dataset sources. J. C. S. Jacques Junior et al, [8] from a computational perspective, speech and writing have been the most thoroughly investigated markers of facts for comprehending character. M. A. Moreno-Armendáriz, et al, [9] A Deep Neural Networks-based model for predicting obvious personality is presented in this paper. It can measure Using the Five-Factor Method, extract personality traits from a portrait picture (Big Five). In order to assess the efficacy of this strategy, a dazzling corpus of 30,935 images was once taken from a current usable supply of movies and annotated with redundant pairwise comparisons to ensure consistency. H. J. Escalante et al., "The article "Modelling, Recognizing, and [10] this article discusses accuracy and comprehension within the context of perceived character recognition. E. Sanchez, et al. [11] In the first step of our procedure, we train a simple Using a collection of unlabelled face movies, a U-net type of model may estimate typical facial dynamics. The construction is then accelerated by using a number of intermediary filters after the common mannequin is frozen. The self-supervised learning is then resumed, but only using specially created movies for each student. A. Kumar, et al [12], and We describe a semi-supervised method in this research for creating a customised classifier from a pre-built generalised classifier in order to improve the precision with which a wearable or portable system user's movement activities are classified. S. Elkosantini, et al. [13] the complexity of intelligent algorithms and the limits of current methods are the driving forces behind this endeavour. In this situation, the current study uses face characteristics to pinpoint fear as a dubious behaviour. E. Granger et al., [14] In this research, we introduce the Deep SiamSRC network, which augments the reference gallery with a few domain-specific facial images

and uses block-sparsity for face matching. Using the methods described by L. Zhang et al. in this study [15], automatic group meeting understanding systems may be able to predict the Big-Five personality characteristics with an average accuracy of 80%. S. Dhelim, et al.[16] The friend encouraged gadget (FRS), which is based on the big-5 model of character traits and hybrid filtering, is existing and examined in this study. Based on user harmony ratings and persona traits, the friend recommended procedure. Y. Wang, e al. [17] then, personality traits are divided into one-factor and two-factor categories using the suggested procedure. The one-factor classification findings show that conscientiousness and neuroticism are strongly correlated with the retrieved facial features. R. K. Moore et al. [18] In this work, we test the ability of four different machine learning algorithms to identify personality traits, and we report our results. A. Chopra, et al. [19] The majority of the records used for this inquiry were gathered using purposeful sampling. The collection, processing, and evaluation of aggregated data from private questionnaires based on the type of professional recreation of the sixty aviation zone personnel is a unique feature of this investigation. M. Katiyar, et al. [20] The previous study involved numerous investigations. To predict the personalities of distinct persons, they employed a range of approaches and algorithms. Some have attempted to determine personality from handwriting using the GSC algorithm. Facial expressions have been used in certain CNN-based experiments. Monalika Padma Reddy, et al. [21] the proposed method's accuracy is compared to that of the existing approaches. The results show that this technique performs better than previously published findings.

3. METHODOLOGY

A field of computer science called artificial intelligence (AI) studies how a machine may carry out jobs that were previously done by people. A particular kind of computer system called artificial intelligence (AI) tries to recognise and duplicate human cognitive processes as well as build machines that imitate human behaviour. Because they possess the information and skills necessary to do so, humans are able to find creative solutions to problems. Computers need information and the capacity for reasoning in order to behave similarly to and as well as people and to have experiences that are comparable to those of people. Intelligence can be seen in the capacity to understand or learn from experience, to take in contradictory and ambiguous information, to unexpectedly and successfully adjust to new circumstances, to solve problems logically, and to solve problems effectively. One of the algorithms is Convolutional Neural Network (CNN) of the deep learning family or deep neural network, performs substantially better on picture data. Convolution neural networks (CNNs), for example, are used in the Deep Learning (DL) Neural Networks technique to accelerate learning in Neural Networks with numerous layers (more than seven levels). The time required for training will be cut in half as a result of the existence of Deep Learning, which will alleviate the issue of losing the gradient in back propagation. Fig 1 The sequential model, one of the patterns developed from the Convolution Neural Networks' general architecture, serves as the foundation for the architecture (CNN). The sequential model performs a convolution pattern and characteristic extraction using the additional layers, specifically a unique convolutional layer. the utilisation of an extractor layer and a strategy to segregate the feature extraction process from the completely linked layer Split Convolution, Global Average Pooling, Batch Normalization, and Data Augmentation are a few of the techniques used to train the CNN model. The convolution layer is built

using a two-dimensional (2D) method with dimensions for top (height) and width (width) based on image input standards (width). The output matrix (dot-product) is entirely based on the kernel filter dimension of each dimension, although this layer maintains parameters in the provided depth dimension (Depth) throughout the activation system. The RELU (Rectified Linear Unit) activation function, which activates the employment of a linear maximum value mechanism, is used in this institution to construct a regularisation method. We employed the openCV package to record live video from the web camera and identify human facial expressions using the Haar-cascade classifier as a resource.

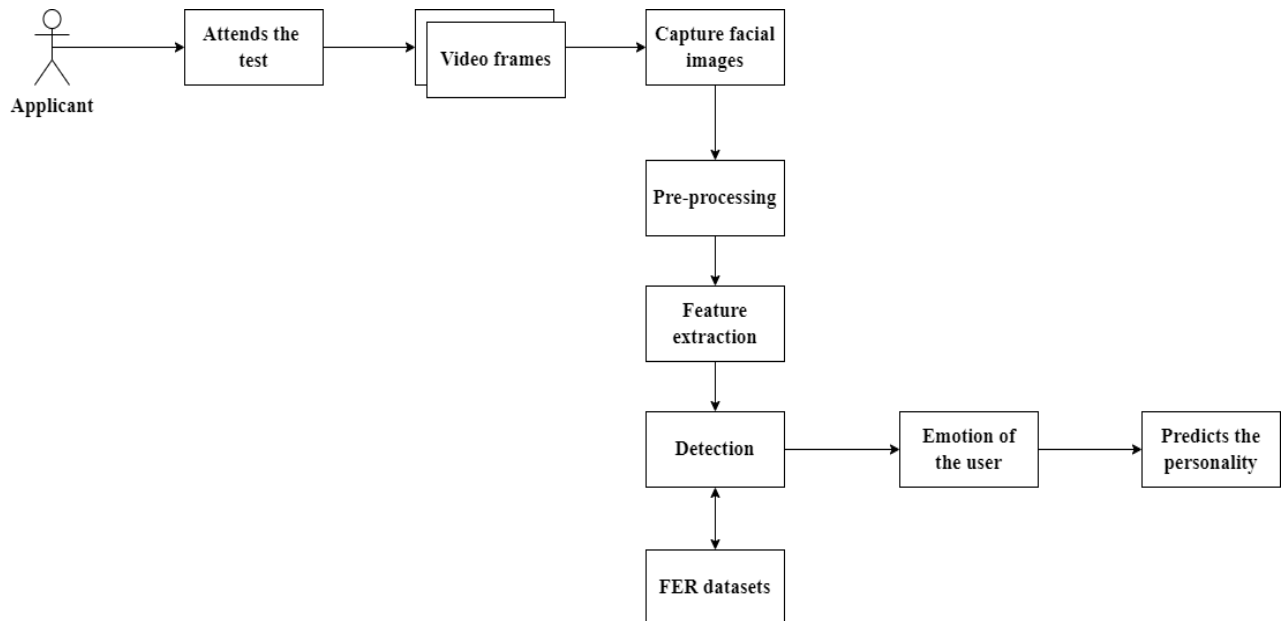


Fig 1: proposed model for personality prediction.

PRE-PROCESSING

Pre-processing aims to enhance some crucial image features and enhance undesired distortions in order to improve image data for subsequent image processing.

Gray-scale conversion: RGB to grayscale conversion Converting an RGB image to a grayscale image is the first step in pre-processing an image. The formula below can be used to multiply the RGB image to obtain it. Fig. 2 depicts the conversion of RGB to grayscale. Brightness is the only information found in a grayscale picture. Each pixel in a grayscale image stands for a distinct volume or amount of light. The grayscale image can also be used to see the brightness gradient. A grayscale image only measures light intensity. The brightness of an 8-bit image will range from zero to 255, with zero signifying black and 255 signifying white. Grayscale conversion transforms a shaded image into a grayscale one. Compared to processing grayscale images, processing colourful images takes longer and involves more effort. To create a grayscale image, all photographic processing methods are used.

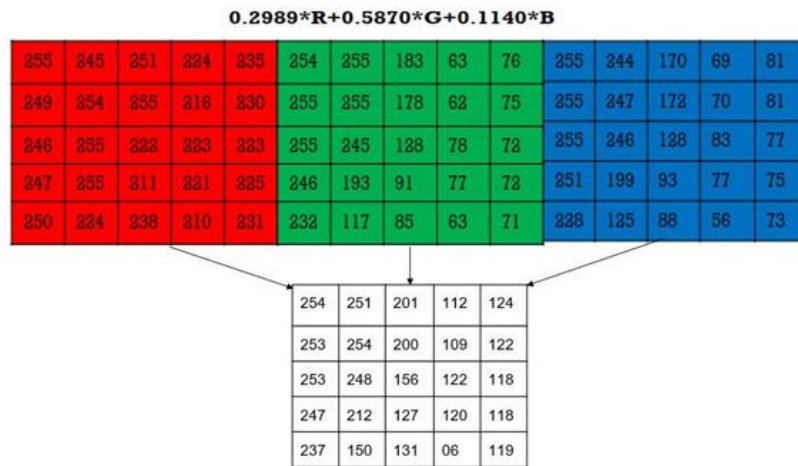


Fig 2: Conversion from RGB to Gray-scale.

Noise removal: The process of finding and removing undesirable noise from a digital image is known as noise control. It can be challenging to distinguish between an image's real-world components and noise-related ones. The duration of random variations in pixel values is known as noise. In our suggested method, To eliminate extraneous noise, we employ a median filter. A nonlinear filter that keeps the edges is the median filter. The median filter is implemented using a sliding window of an odd length. The filter output is the median of the patterns detected in the window, and each pattern cost is ranked by magnitude.

Feature extraction: As shown in Fig. 3, we used the OpenCV package to collect real-time web camera footage and the Haar Cascades method to identify applicants' faces. The Adaboost learning algorithm, which is utilised by Haar Cascades, was created by Freund et al., who's work earned them the 2003 Gödel Prize. In order to build an effective set of classifiers, the Adaboost learning method narrowed down a large number of crucial components from a large set. We utilised TensorFlow and the Keras high-level API to build a Convolutional Neural Network model. The images were all resized to 640 pixels wide, and the peak of each image was calculated using the 420-pixel pixel ratio of the imaging device. Using the face detection haar cascade classifier, the facial points of every body within a 5-second period have been retrieved. We changed all of the photos to grayscale in order to improve photo classification and remove background distractions like hair and makeup.

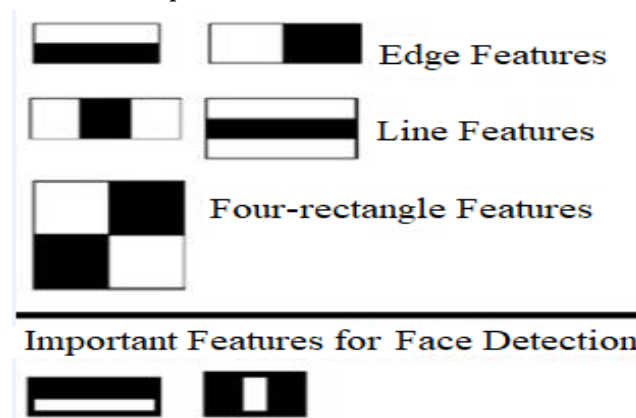


Fig 3: Face recognition using Haar cascade.

Prior to cropping and normalising the input image to a size of 4848 pixels, the algorithm first identifies the face in the image. Then, CNN receives these facial photographs as input. The output of facial expression recognition is the ultimate outcome (anger, happiness, sadness, disgust, surprise, or neutral). Figure 4 depicts the general layout of our suggested approach.

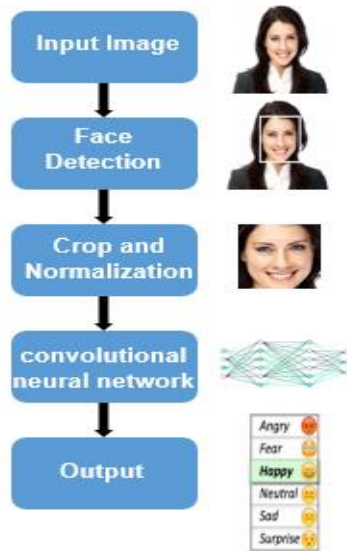


Fig 4: Structure of facial expression recognition system.

LAYERS OF CNN

CONVOLUTION LAYER: Convolutional Layer: Convolution layers are used to construct a small portion of the image after the image has been scanned by the computer as pixels. These images or patches are referred to as features or filters. These filters are compared to the brand-new input photos, and if they match, the image is correctly classified.

RELU LAYER: The rectified linear unit (ReLU) layer removes all incorrect costs from the filtered snapshots and replaces them with zeros. The values are finished here to avoid adding to zeroes. This radical change feature only prompts a node if the input price is larger than a positive integer and the enter value is less than zero; otherwise, the output is zero and the matrix is cleaned of any incorrect values.

POOLING LAYER: In this layer, the image's size is constrained or reduced. We begin by selecting the size of the window, then specify the ideal stride, and lastly stroll the window across your filtered pictures. Take the highest values from each window after that. Through layer pooling, the matrix's size and the number of images will both be decreased. The decreased metric vector serves as the source for the fully linked layer.

FULLY CONNECTED LAYER: The fully linked layer that was utilized to classify the input image. Unless you have a 2x2 matrix, you'll need to repeat these layers if necessary. Finally, the completely connected layer is used to perform the actual categorization.

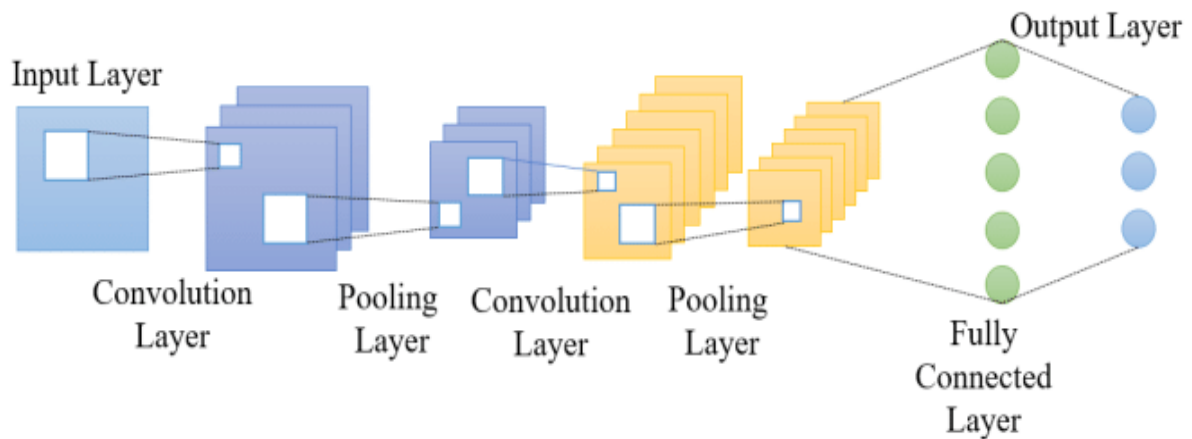


Fig 5: Typical CNN architecture

DATASETS

DATASETS Our Convolutional Neural Network model, which addresses seven emotions, was trained using the FER 2013 database (happiness, anger, sadness, disgust, neutral, fear and surprise). Before being used as inputs by the CNN model, the recognised face photographs were scaled to 48x48 pixels and made into grayscale images.

Angry dataset: Fig 6: represents the happy dataset, where around 3,995 angry datasets have been collected from the FER 2013 database. A smile is a facial expression that might indicate An upward curve of the cheekbones and a smile made by the sides or edges of the lips indicate that someone is happy or enjoying something.



Fig 6: Angry dataset

Disgust dataset: Fig 7: represents the disgust dataset, where around 436 disgust datasets have been collected from the FER 2013 database. A person who has a disgusted expression on his face as a result of seeing something strange or hearing something unimportant. When the top lip rises and the area around the nose bridge creases, it's an indication of distaste.



Fig 7: Disgust dataset

Fear dataset: Fig 8: represents the fear dataset, where around 4,097 fear datasets have been collected from the FER 2013 database. When someone is unable to handle a situation or is in a terrifying setting, they communicate their fear. Fear is shown on a person's face by simultaneously lifting both brows, drawing in the eyelids, and horizontally opening the lips.



Fig 8: Fear dataset

Happy dataset: Fig 9: represents the happy dataset, where around 7,215 happy datasets have been collected from the FER 2013 database. A smile is a facial expression that might indicate that something makes someone happy or enjoyable. The muscles in the cheeks and the margins or sides of the lips move upward to form a smile, which is the defining feature of the happy expression.



Fig 9: Happy dataset

Neutral dataset: Fig 10: represents the neutral dataset, where around 4,965 neutral datasets have been collected from the FER 2013 database. The facial expression of someone who is arrogant and lacks respect for others frequently underestimates others. The expression can be seen when one corner of the mouth is raised.



Fig 10: Neutral dataset

Sad dataset: Fig 11: represents the sad dataset, where around 4,830 sad datasets have been collected from the FER 2013 database. A sad face appears when there is unhappiness or a sensation of missing something. The lips are drawn downward, the upper eyelid droops, and the eye loses focus, this is what a sad facial expression looks like. The upper eyelid droops, the lips are dragged downward, and the eye becomes out of focus.



Fig 11: Sad dataset

Surprise dataset: Fig 12: represents the surprise dataset, where around 3,171 sad datasets have been collected from the FER 2013 database. When someone is caught off guard by a sudden, unexpected, or significant occurrence or message, they express

surprise. The raised eyebrows, wide open eyes, and mouth opening reaction portray a shocked expression.



Fig 12: Surprise dataset

RESULTS AND DISCUSSIONS

In this study, the system was put through several stages of testing for the design recognition of facial micro expressions. The results showed that a face expression detection system can effectively and instantly apply the CNN architectural model. The data training can be carried out perfectly using a separate convolution layer, according to the evidence, and the trained model's face expression has an average data accuracy of 89.32 percent. Once the system has been implemented, it is crucial to evaluate the results. The results of this test are displayed in table I.

Model	Performance			
	Precision	Recall	F1-score	Accuracy
Proposed model	86.09	82.31	79.23	89.32
VGG-16 Res-Net model	90.33	60.23	74.21	74.89
Emotion detection model	88.11	77.2	55.12	76.23
Image-Net Pre-trained model	74.89	71.70	75.29	66.45

Table 1: Performance comparison of models.

I. Facial expression prediction test

This test will determine how well the system recognises previously learned face expressions. The system recognises the user's face with a success rate of 94.28 percent, hence it can be concluded that the system performs well. Figure 12 shows an sample of the face expression recognition testing results. The scan was repeated fifteen times for each expression in accordance with the accuracy of the examinations for angry, disgusted, sad, happy, fearful, neutral, and surprised. The system successfully recognised each and every assessment. There was one error in the display of wrath, two in the expressing of disgust, and one in the presentation of concern. Figure 13 illustrates how accurately each persona attribute was captured.

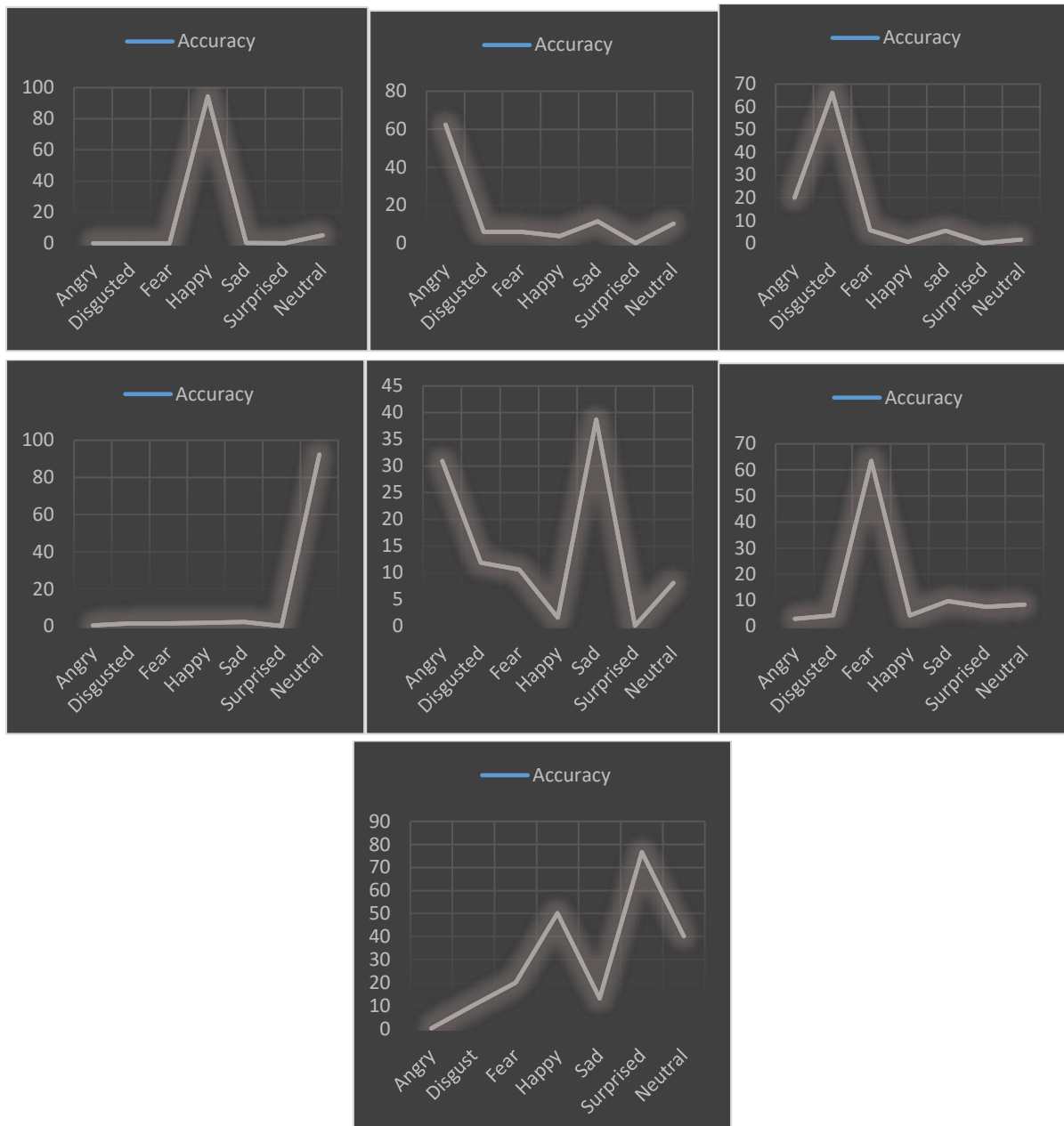
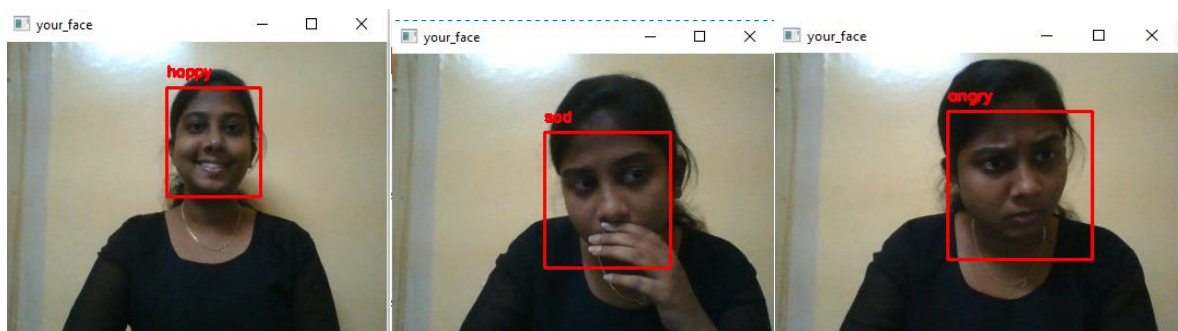


Fig 13: Represents the accuracy graphs for each personality traits.



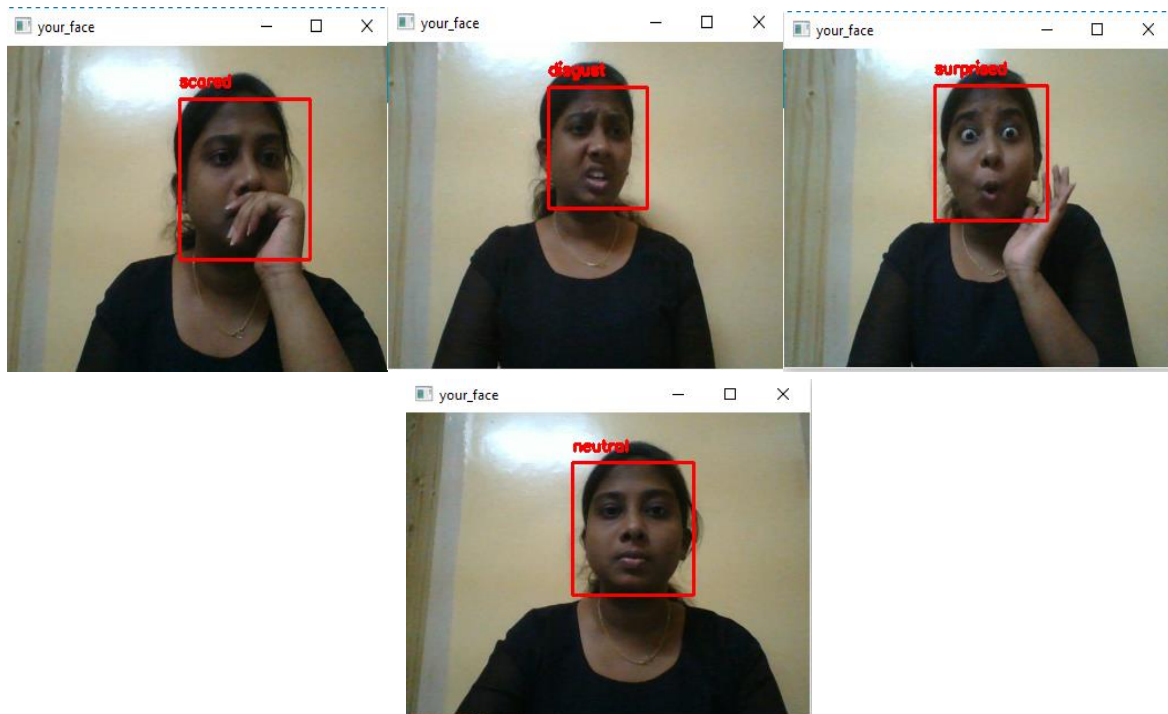


Fig 14: Represents the facial expression recognition

The recognised face photographs were scaled to 4848 pixels and made into grayscale images. Fig 14: represents the probabilities for each of the personalities, the overall accuracy is based on the probability. I have been developed the front end part with the use of Tkinter for the purpose of online interview for the job applicants requirement, when the applicant attends the online interview by the valid username and password automatically captures the still images of the applicant with the use of camera. At the end the applicant will be selected for the job role based on the personality characteristics and the marks obtained by the applicant.

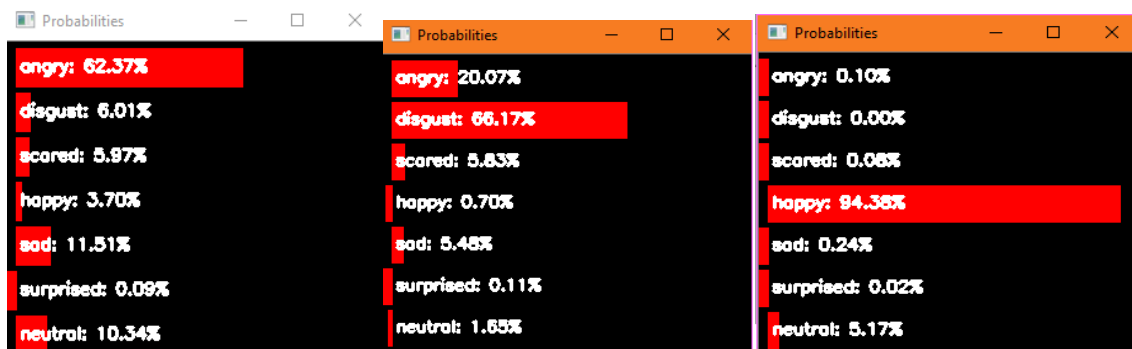




Fig 15: Probability for each personalities.

CONCLUSION

We provide a Convolutional Neural Network model for identifying applicant facial expressions in this paper. Four convolutional layers, four max pooling layers, and two completely related layers make up the suggested model. The system recognises faces in photographs submitted by applicants and categorises them using a Haar-like detector into seven distinct facial expressions: surprise, fear, disgust, sad, happy, angry, and neutral. On the FER 2013 database, the proposed model has an accuracy rate of 89 percent. Our facial expression recognition technology can help HR determine how an employee feels about his presentation. In order to extract emotions from 3D candidates' faces, we'll focus on employing a Convolutional Neural Network model in the future.

REFERENCES

- [1] R. Subramanian, J. Wache, M. K. Abadi, R. L. Vieriu, S. Winkler and N. Sebe, "ASCERTAIN: Emotion and Personality Recognition Using Commercial Sensors," in *IEEE Transactions on Affective Computing*, vol. 9, no. 2, pp. 147-160, 1 April-June 2018, doi: 10.1109/TAFFC.2016.2625250.
- [2] J. A. Miranda-Correa, M. K. Abadi, N. Sebe and I. Patras, "AMIGOS: A Dataset for Affect, Personality and Mood Research on Individuals and Groups," in *IEEE Transactions on Affective Computing*, vol. 12, no. 2, pp. 479-493, 1 April-June 2021, doi: 10.1109/TAFFC.2018.2884461.
- [3] R. D. P. Principi, C. Palmero, J. C. S. J. Junior and S. Escalera, "On the Effect of Observed Subject Biases in Apparent Personality Analysis From Audio-Visual Signals," in *IEEE Transactions on Affective Computing*, vol. 12, no. 3, pp. 607-621, 1 July-Sept. 2021, doi: 10.1109/TAFFC.2019.2956030.
- [4] F. Zhang and F. Wang, "Exercise Fatigue Detection Algorithm Based on Video Image Information Extraction," in *IEEE Access*, vol. 8, pp. 199696-199709, 2020, doi: 10.1109/ACCESS.2020.3023648.

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- [5] P. Thiam et al., "Multi-Modal Pain Intensity Recognition Based on the SenseEmotion Database," in *IEEE Transactions on Affective Computing*, vol. 12, no. 3, pp. 743-760, 1 July-Sept. 2021, doi: 10.1109/TAFFC.2019.2892090.
 - [6] S. Escalera, X. Baró, I. Guyon and H. J. Escalante, "Guest Editorial: Apparent Personality Analysis," in *IEEE Transactions on Affective Computing*, vol. 9, no. 3, pp. 299-302, 1 July-Sept. 2018, doi: 10.1109/TAFFC.2018.2864230.
 - [7] L. Zhang, S. Peng and S. Winkler, "PersEmon: A Deep Network for Joint Analysis of Apparent Personality, Emotion and Their Relationship," in *IEEE Transactions on Affective Computing*, vol. 13, no. 1, pp. 298-305, 1 Jan.-March 2022, doi: 10.1109/TAFFC.2019.2951656.
 - [8] J. C. S. Jacques Junior et al., "First Impressions: A Survey on Vision-Based Apparent Personality Trait Analysis," in *IEEE Transactions on Affective Computing*, vol. 13, no. 1, pp. 75-95, 1 Jan.-March 2022, doi: 10.1109/TAFFC.2019.2930058.
 - [9] M. A. Moreno-Armendáriz, C. A. Duchanoy Martínez, H. Calvo and M. Moreno-Sotelo, "Estimation of Personality Traits From Portrait Pictures Using the Five-Factor Model," in *IEEE Access*, vol. 8, pp. 201649-201665, 2020, doi: 10.1109/ACCESS.2020.3034639.
 - [10] H. J. Escalante et al., "Modeling, Recognizing, and Explaining Apparent Personality From Videos," in *IEEE Transactions on Affective Computing*, vol. 13, no. 2, pp. 894-911, 1 April-June 2022, doi: 10.1109/TAFFC.2020.2973984.
 - [11] S. Song, S. Jaiswal, E. Sanchez, G. Tzimiropoulos, L. Shen and M. Valstar, "Self-supervised Learning of Person-specific Facial Dynamics for Automatic Personality Recognition," in *IEEE Transactions on Affective Computing*, doi: 10.1109/TAFFC.2021.3064601.
 - [12] G. Singh, M. Chowdhary, A. Kumar and R. Bahl, "A Personalized Classifier for Human Motion Activities With Semi-Supervised Learning," in *IEEE Transactions on Consumer Electronics*, vol. 66, no. 4, pp. 346-355, Nov. 2020, doi: 10.1109/TCE.2020.3036277.
 - [13] M. Ben Ayed, S. Elkosantini, S. A. Alshaya and M. Abid, "Suspicious Behavior Recognition Based on Face Features," in *IEEE Access*, vol. 7, pp. 149952-149958, 2019, doi: 10.1109/ACCESS.2019.2947338.
 - [14] F. Mokhayeri and E. Granger, "Video Face Recognition Using Siamese Networks With Block-Sparsity Matching," in *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 2, no. 2, pp. 133-144, April 2020, doi: 10.1109/TBIOM.2019.2949364.
 - [15] L. Zhang et al., "Multiparty Visual Co-Occurrences for Estimating Personality Traits in Group Meetings," 2020 IEEE Winter Conference on Applications of Computer Vision (WACV), 2020, pp. 2074-2083, doi: 10.1109/WACV45572.2020.9093642.
 - [16] H. Ning, S. Dhelim and N. Aung, "PersoNet: Friend Recommendation System Based on Big-Five Personality Traits and Hybrid Filtering," in *IEEE Transactions on Computational Social Systems*, vol. 6, no. 3, pp. 394-402, June 2019, doi: 10.1109/TCSS.2019.2903857.
 - [17] M. Xue, X. Duan, Y. Wang and Y. Liu, "A Computational Personality Traits Analysis Based on Facial Geometric Features," 2019 IEEE 14th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), 2019, pp. 1107-1111, doi: 10.1109/ISKE47853.2019.9170334.
 - [18] D. Al-Hammadi and R. K. Moore, "Using Sampling Techniques and Machine Learning Algorithms to Improve Big Five Personality Traits Recognition from Non-

verbal Cues," 2021 National Computing Colleges Conference (NCCC), 2021, pp. 1-6, doi: 10.1109/NCCC49330.2021.9428804.

[19] D. Mansour, A. B. Bhardwaj and A. Chopra, "Relating OCEAN (Big Five) to Job Satisfaction in Aviation," 2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), 2021, pp. 285-289, doi: 10.1109/ICCIKE51210.2021.9410720.

[20] B. K. Singh, M. Katiyar, S. Gupta and N. G. Ganpatrao, "A Survey on: Personality Prediction from Multimedia through Machine Learning," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021, pp. 1687-1694, doi: 10.1109/ICCMC51019.2021.9418384.

[21] Padma Reddy, Monalika & Selvam, Sheba & Ac, Meghana & Na, Ashwitha. (2021). Human Activity Recognition using 3D CNN. 10.13140/RG.2.2.20520.49923.

[22] Yedilkhan, Amirgaliyev, et al. "Predicting heating time, thermal pump efficiency and solar heat supply system operation unloading using artificial neural networks." *International Journal of Mechanical and Production Engineering Research and Development* 9.6 (2019): 221-232.

[23] Kekan, ABHIJEET H., and B. Raghu Kumar. "Crack depth and crack location identification using artificial neural network." *Int. J. Mech. Product. Eng. Res. Develop* 9.2 (2019): 699-708.

[24] Mofleh, Ahmed F., Ahmed N. Shmroukh, and NOUBY M. GHAZALY. "Fault detection and classification of spark ignition engine based on acoustic signals and artificial neural network." *International Journal of Mechanical and Production Engineering Research and Development* 10.3 (2020): 5571-5578.

[25] Ramachandran, Vedantham, E. Srinivasa Reddy, and B. Sivaiah. "An enhanced facial expression classification system using emotional back propagation artificial neural network with DCT approach." *Int. J. Comput. Sci. Eng. Inf. Technol. Res.(IJCSEITR)* 5 (2015): 83-94.

[26] Bagalkote, Ismail S., and ANUP S. VIBHUTE. "Multiresolution Analysis and Implementation of Grape Species Classification Using Neural Network." *International Journal of Agricultural Science and Research (IJASR)* 6 (2016): 37-46.

[27] Deshpande, P. S., and J. S. Chitode. "Transformation coding for emotion speech translation: a review." *International Journal of Electrical and Electronics Engineering Research (IJEEER)* 6.1 (2016): 1-12.