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"EMOTION RECOGNITION USING FACIAL EXPRESSION ANALYSIS"

Naorem Tikendrajit Singh,

Research Scholar, Department of Mathematics, School of Science,

Glocal University, Saharanpur.

Dr Uma Shanker,

Associate Professor, Department of Mathematics, School of Science,

Glocal University, Saharanpur.

ABSTRACT

Humans have a built-in capacity to recognise and respond to the feelings of others. We must, however, overcome the challenge of emotion detection in order to construct a humanoid "robot" that can connect and emote with human partners. A computer's capacity to understand human emotions has several practical uses in the real world. People who are unable to care for themselves may benefit from the use of therapeutic robots. An individual patient's present and changing mental state of mind might be used to modify patient care and engagement techniques by these technologies. When a patient feels disturbed or dissatisfied, for example, a more beneficial method may be to acknowledge the feeling and express compassion. Using an Android application, we demonstrate how to discern seven different sorts of emotions in digital photographs (neutral-happy- sad- surprised- afraid- angry- disgusted). For each of six participants, coefficients defining face expressions were employed as features. For a three-dimensional facial model, the features have been estimated. The k-NN classifier and MLP neural network were used to classify the features.OpenCV, Fisher's algorithm, and Java language were used to build the server for the Android application, which compares the coordinates of the eyes and mouth in the test image with the coordinates in the database to take the most similarity and display it. We also built a Java server to implement the android application. This work was created in Java using NetBeans IDE 8.0.2 and Android Studio to construct Android applications.

KEYWORDS: Recognition of Emotional Facial Expressions, Software Evaluation, Human Emotion Recognition,Automatic Facial Coding, Facial Expression Recognition, Specific Emotions.

1. INTRODUCTION

A person may be recognized by their facial expressions, which are utilized in nonverbal communication and for emotion identification. They rank right up there with the tone of voice in terms of importance in everyday emotional communication. They are also a sign of a man's emotional condition, letting him to convey his sentiments. A person's emotional condition may be readily discerned by others. Therefore, facial expressions are often employed in automated systems for recognizing emotions. The study reported in this article aims to distinguish seven main emotional states based on facial expressions: neutral, pleasure, surprise, anger, sorrow, fear, and disgust. Computer vision systems (often cameras) may be used to examine the picture of the face for identifying emotions since the face is the most exposed area of the body. The quality of emotion detection systems based on cameras is influenced by variables such as lighting and head position. 2D image analysis algorithms are particularly susceptible to these issues. The methods used to create 3D face models show far greater promise. Because of its cheap cost and ease of use, we chose Microsoft Kinect for our 3D face modelling research. However, the Kinect has a rather fast rate of picture registration (30 frames per second) despite its low scanning resolution. It contains two cameras and an infrared emitter. While one of the cameras captures images in visible light, the other is equipped with an infrared sensor and is used to gauge depth. Users can create a 3D model of their face by reflecting infrared rays off of their own bodies. Based on 121 points acquired by the Kinect sensor, the model is created. These points are placed in a variety of locations on the face, including the corners of the mouth, the nose, the cheekbones, and the eyebrows. 2D representation of the face's distinctive features. A matrix is used to hold the points' spatial coordinates. As specified by Kinect, the Kinect device's coordinate system. Ekman and Friesen's FACS method (Facial Action Coding System) uses Action Units (AUCs) to describe changes in facial expressions caused by the activation of certain muscles (AU). The coefficient, for example, describes the movement of the inner section of the eyebrow, which is controlled by the frontal cranial vault muscle.

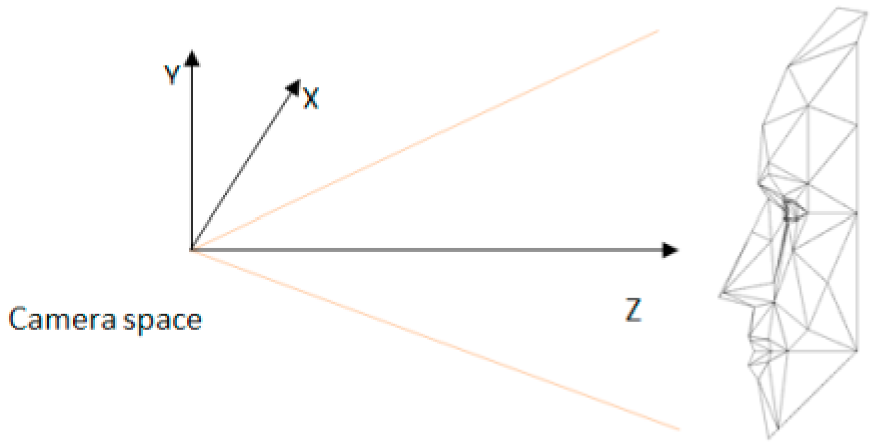

Figure 1: Kinect coordinate system

This system delivers six Action Units (AU) from the FACS system, which may be accessed by the Kinect device. Emotions may be described using Action Units alone or in combination. An upper lip rising, jaw lowering, lip stretching, lowering of the eyebrows, lip corner depressing, and lifting of the outer eyebrows are all examples of AUs.

2. LITERATURE REVIEW

Amjad Rehman Khan (2022): Researchers are focusing on the development of facial emotion recognition (FER) as a promising new field of study. Nonverbal communication plays a huge part in everyday life, accounting for 55-93% of all communication. In surveillance films, expression analysis, gesture recognition, smart homes, computer games, depression therapy, patient monitoring, anxiety, lie detection, psychoanalysis, paralinguistic communication, tiredness detection in operators, and robotics, facial emotion analysis is very effective. Here, we provide a comprehensive overview of FER. The literature is drawn from a variety of credible studies published in the last decade. Conventional machine learning (ML) and a variety of deep learning (DL) methodologies are used in this evaluation. Furthermore, a variety of publicly accessible assessment metrics datasets are reviewed and compared to benchmark findings.

Theresa Küntzler et. al, (2021): Researchers can learn a lot about a person's emotional condition by observing their facial expressions. Automated Facial Expression Recognition is getting a technical boost thanks to recent developments (FER). An advanced technique like this one may greatly enhance the quantity of data that can be analysed using machine learning. FER may currently be used to classify standardised prototype facial expressions, and it has been shown to be reliable. In terms of realistic face expressions, the application of this technique is as yet undetermined; It is therefore necessary to test and compare the performance of three different facial emotion recognition systems (Azure face API from Microsoft; a face++

from Megvii Technology; and Face Reader from Noldus Information Technology), as well as their ability to recognise human emotions in posed and non-posed facial expressions (from prototypical inventories) (extracted from emotional movie scenes). This means that all three algorithms correctly categorise fundamental emotions (Face Reader is the most accurate), and they are generally on par with human raters. For non-standardized stimuli, all three systems' performance reduces significantly, but Azure still performs comparable to humans. Some non-standardized emotional facial expressions are incorrectly categorized as neutral by all systems and people alike.

D Y Liliana (2019): Automatic facial expression recognition is actively emerging research in Emotion Recognition. This paper extends the deep Convolutional Neural Network (CNN) approach to facial expression recognition task. This task is done by detecting the occurrence of facial Action Units (AUs) as a subpart of Facial Action Coding System (FACS) which represents human emotion. In the CNN fully-connected layers we employ a regularization method called “dropout” that proved to be very effective to reduce over fitting. This research uses the extended Cohn Kanade (CK+) dataset which is collected for facial expression recognition experiment. The system performance gain average accuracy rate of 92.81%. The system has been successfully classified eight basic emotion classes. Thus, the proposed method is proven to be effective for emotion recognition.

A.L.I. Ghali & Mohamad-Bassam Kurdy (2018): Humans have a built-in capacity to recognise and respond to the feelings of others. We must, however, overcome the challenge of emotion detection in order to construct a humanoid "robot" that can connect and emote with human partners. A computer's capacity to understand human emotions has several practical uses in the real world. People who are unable to care for themselves may benefit from the use of therapeutic robots. An individual patient's present and changing mental state of mind might be used to modify patient care and engagement techniques by these technologies. When a patient feels disturbed or dissatisfied, for example, a more beneficial method may be to acknowledge the feeling and express compassion. Working with computers that can perceive and react to emotional state, even if they are not robots, may go a long way to improving human-computer interaction quality (HCI).

Paweł Tarnowski et. al, (2017): The findings of identification of seven emotional states (neutral, pleasure, sorrow, surprise, anger, fear, and disgust) based on facial expressions are described in the article. For each of six participants, coefficients defining face expressions were employed as features. Three-dimensional facial model features have been computed. The k-NN classifier and MLP neural network were used to classify the features.

3. METHODOLOGY

We examine emotional facial expressions using three distinct facial expression recognition methods and human emotion recognition data. Static picture inventories of actors who were coached to exhibit archetypal emotional expressions as well as an inventory of actors expressing more genuine emotional facial expressions in movie stills were analysed as an approximation to standardised and non-standardized facial expressions. Probability parameters are derived from all instruments to represent the manifestations of common human emotions such as happiness, annoyance, sorrow, rage and fear. Data from human raters who scored subsets of the same photos serves as our standard for the system.

Images of Facial Expressions

On standardized and non-standardized emotional facial expressions in still photos, we evaluate several FER methods, as well as human face recognition data. Emotional face expression photographs of the most common emotions are included in the entire chosen inventory, which may be used for research purposes. Using both standardized and non-standardized data, the dropout rates for the three FER tools are shown in Table 1.1, along with the corresponding emotion categories and image distributions.

Table 1

Category distributions of test data and drop outs of Azure, Face++, and Face Reader.

	Standardized data							
	Neutral	Happy	Sad	Fear	Angry	Surprise	Disgust	Overall
Absolute frequency of images	178	178	178	178	178	178	178	1246
Relative frequency of images	14.3	14.3	14.3	14.3	14.3	14.2	14.2	100
	Drop out rates (percent per category)							
Face++	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Azure	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
FaceReader	0.6	0.0	0.0	1.1	1.1	2.2	1.2	0.88
	Non-standardized data							
	Neutral	Happy	Sad	Fear	Angry	Surprise	Disgust	Overall
Absolute frequency of images	236	270	245	143	254	151	88	1387
Relative frequency of images	17.0	19.5	17.7	10.3	18.3	10.9	6.3	100
	Drop out rates (percent per category)							
Face++	0.0	0.7	0.8	0.7	0.4	0.0	1.1	0.5
Azure	16.9	11.1	25.3	26.6	25.2	17.9	23.9	20.3
FaceReader	73.3	70.0	75.1	79.0	76.8	74.8	69.3	74.2

These standardized facial expressions are photos taken under controlled settings (such as appropriate lighting, frontal head orientations, and a focused perspective) and show prototype expressions of certain emotions. The four databases that make up the archetypal pictures are used in order to increase the number of photos and add more variation. Male and female subjects aged between 20 and 30 are included in the Karolinska Directed Emotional Faces (Lundqvist et al., 1998). A total of 562 x 762 frontal photos is used in this investigation. There are photographs of the facial expressions of 20 men and 19 women of Caucasian ethnicity in the Radboud Faces Database. Photographs shot frontally (at a resolution of 681 1,024) were utilized with the subgroup of adult models who were looking directly into the camera. Still images from the Amsterdam Dynamic Facial Expression Set (resolution: 720 x 576). A distinction is made between Northern European (12 models) and Mediterranean (5 female) models (10 models, 5 of them female; Van der Schalk et al., 2011). An emotive face expression set from Warsaw includes photos of 40 models (16 ladies and 14 guys). A total of 1,725 x 1,168 images is utilized in this investigation (frontal images). Overall, there are 1,246 photos that are equally divided over the various emotion categories.

Data for non-standardized face expressions came from a benchmark test for more realistic computer vision research. Stills from movie sequences with actors' expressions are included in the Static Facial Expression in the Wild (SFEW) data collection. "Harry Potter" and "Hangover" are good examples of this kind of film. This research makes use of the most recent iteration. Closed captions and subtitles for the deaf and hard of hearing were used to create the data. While the spoken word is included in the text itself, other noises such as laughing are also included. In order to identify emotional content, the subtitles were mechanically scanned for emotional terms. Finally, the final selection of emotional facial expressions for this questionnaire was identified and confirmed by professional human coders. In order to assess the systems' performance on photographs that are not normal and not shot under usual settings, we utilize these images (variable lighting and head positions). Emotion categories are unevenly distributed across the 1,387 photos (resolution: 720 x 576). (Minimum of 88 images for disgust and a maximum of 270 images for joy).

Facial Expression Recognition Tools

We evaluate the Microsoft Azure Face API (Version 1.0, Microsoft), Megvii Technology's Face++ (Version 3.0), and Face Reader (Version 3.0, Megvii Technology) (Version 8.0, Noldus Information Technology). A free membership is available for the first two APIs. In the scientific world, Face Reader is a well-known application that may be installed locally on a computer. Face detection, face verification, and emotion recognition are some of the features available in each of the systems that may be used to analyze photos. Neutral, pleasure, sadness; anger; disgust; fear; and surprise all have likelihood ratings. Face++, on the other hand, employs a scale from 1 to 100 instead of the 0 to 1 used by Azures and Face Reader. Thus, Face++ ratings are rescaled from 0 to 1. It's recommended to delete photographs if the quality of face recognition is too poor, provided by Face Reader's extra quality parameter as a result, all photos with a quality value of less than 70% have been removed.

Human Emotion Recognition

Humans rated 2,633 photos, each of which had up to 127 random subsamples, in an online survey in order to gather data for FER's benchmark. Excluded from further analysis are individuals who evaluated less than 20 photographs (17 participants rated between 20 and 126 pictures). That means there were 101 people who assessed an average of 116.1 photos out of a possible 291 (SDage = 9.1). Twenty-five photographs were chosen at random and no one (less than one percent of participants) assessed them. Facial expressions were categorized as neutral, pleasure or sorrow or wrath and contempt or fear and surprise by participants. There were several options available to the user. On a 7-point Likert scale, the authenticity of the conveyed emotion was scored (1 -very in-genuine, 7 -very genuine). To make it easier to compare the results to the statistic offered by the FER tools, all evaluations are averaged per picture. For the sincerity evaluations, we may calculate percentages of emotion ratings and average values per picture.

Six action units (AU) generated by the Kinect gadget were employed as characteristics in the categorization procedure. Examples of AU values for one participant's facial expressions are shown in Table 2. Anger, astonishment, grief, fear, and contempt are all represented by the photos.

Table 2

The facial expressions and corresponding AU

ES	NEUTRAL	JOY	SURPRISE	ANGER	SADNESS	FEAR	DISGUST
AU0	0.21	0.77	-0.10	0.30	0.17	-0.11	0.91
AU1	-0.06	0.09	0.60	-0.07	-0.04	0.20	0.13
AU2	-0.25	1.00	-0.49	0.06	-0.37	-0.60	0.88
AU3	-0.21	0.00	-0.13	0.04	-0.09	-0.17	0.00
AU4	-0.04	-0.47	0.58	-0.19	-0.02	0.28	-0.32
AU5	-0.23	-0.30	0.10	-0.34	-0.27	-0.02	-0.39

Figure 2 shows an example of the AU2 and AU5 distributions for subject #3. Even a cursory look at the distribution of the traits reveals that we are capable of identifying the emotions of certain individuals. AU was used to investigate whether or not emotion detection could be done in an automated fashion. K-NN and MLP classification models were used in the trials.

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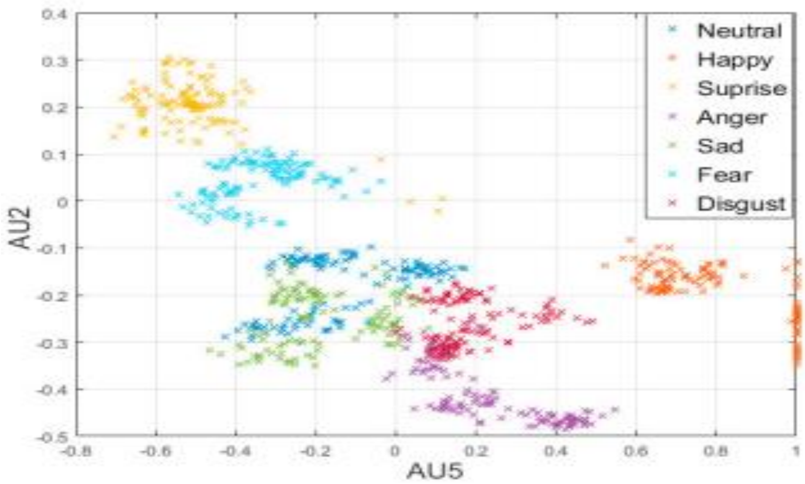

Figure 2: AU2 and AU5 distribution

First-second signal quality may be impacted by user reaction time and the time it takes to establish a correct facial expression. As a result, only AUs collected in the last four seconds of each emotional state presentation were utilized to train a classifier. Neural networks with seven neurons in the hidden layer were employed in the 3-NN and MLP classifications. Figure 2 depicts the neural network utilized in the experiment. There was six AU of input for the network. One of the seven emotional states was the result.

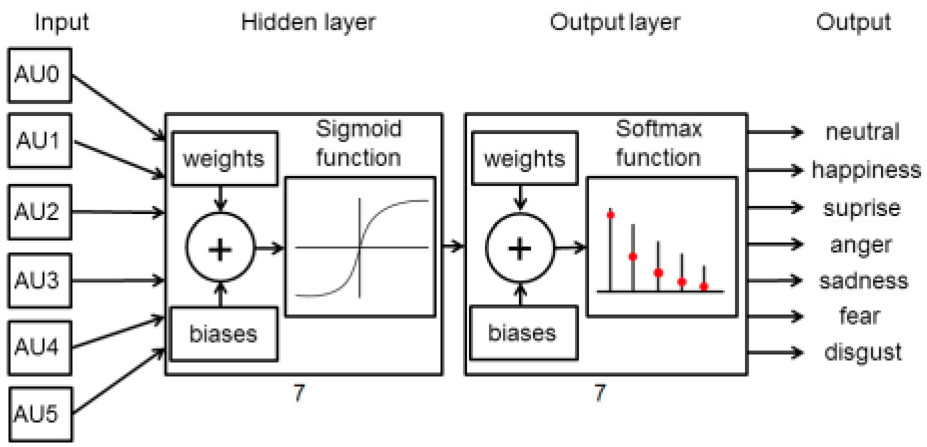

Figure 3: The neural network structure

4. ANALYSIS

Subject-independent emotion recognition was evaluated for all users at the same time. 3-NN and MLP datasets were split into two groups: one for teaching (70 percent) and the other for evaluation (30 percent) and validation (15 percent) respectively (15 percent). Using the back propagation technique and the conjugate gradient approach, we built a neural network. Table 3 displays the categorization findings for the subject-dependent instance.

Table 3:

The results of the subject-dependent classification

Subject	MLP	3-NN
1	0.94	0.97
2	0.96	0.96
3	0.90	0.98
4	0.74	0.90
5	0.96	0.96
6	0.93	0.97
Average	**0.90**	**0.96**

As a general rule, facial expression recognition for all users is more helpful and adaptable than for a single user (subject-dependent). The classifier accuracies (CA) for 3-NN and MLP algorithms were 95.5 percent and 75.9 percent, respectively, in the subject-independent method. The 3-NN classifier results are really impressive. In this instance, the confusion matrices must be calculated in order to establish which emotions are the simplest to discern and which are the most difficult. Tables 4 and 5 show the confusion matrices for 3-NN and MLP classifiers, respectively.

Table 4:

Confusion matrix for 3-NN classifier (CA=0.95)

Emotions	Neutral	joy	surprise	anger	sadness	fear	disgust
neutral	425	2	1	3	10	0	1
joy	9	421	0	2	6	0	5
surprise	1	1	429	0	0	11	0
anger	7	1	0	428	1	0	6
sadness	20	4	0	2	416	1	0
fear	5	0	19	0	6	412	1
disgust	2	2	1	9	2	0	427

Table 5:

Confusion matrix for MLP classifier (CA=0.75)

Emotions	Neutral	joy	surprise	anger	sadness	Fear	disgust
neutral	1130	65	1	40	505	4	45
joy	61	1102	0	68	149	0	124
surprise	0	0	1056	4	0	194	13
anger	47	157	0	1317	30	0	90
sadness	193	41	15	4	726	77	21
fear	4	2	404	0	55	1201	3
disgust	41	109	0	43	11	0	1180

Another data segment will be classified in the following phase of our research (for learning and testing). Use of "natural" data divisions has resulted in classification conditions that are closer to the actual thing. Six subsets (2 sessions x 3 trials) of data with all seven facial expressions were used for subject-dependent categorization (see Fig.). Classifier instruction was carried out using five subsets, while testing was carried out with only one. Table 6 displays the average classification outcomes for the MLP and 3-NN classifiers.

Table 6:

The accuracy of the subject-dependent classification for "natural" division of data

Subject	MLP	3-NN
1	0.75	0.70
2	0.80	0.74
3	0.71	0.69
4	0.57	0.48
5	0.79	0.76
6	0.74	0.85
Average	**0.73**	**0.70**

With respect to subject-independent categorization, 12 subgroups were created. Each subset included data from just one user's session. Eleven of the subsets were used to train classifiers, while one was used to assess them. A summary of all of the individual classifications is provided in Table 7.

Table 7:

The accuracy of subject-independent classification for "natural" division of data

No	Subject-Session	MLP	3-NN
1	1-A	0.74	0.67
2	1-B	0.76	0.57
3	2-A	0.76	0.68
4	2-B	0.85	0.70
5	3-A	0.65	0.64
6	3-B	0.76	0.63
7	4-A	0.60	0.36
8	4-B	0.55	0.31
9	5-A	0.80	0.77
10	5-B	0.78	0.72
11	6-A	0.81	0.80
12	6-B	0.67	0.68
	Average	**0.73**	**0.63**

For user-independent categorization, the MLP neural network attained the greatest classification accuracy (73%). In such situation, the findings of all subjects were added together to form cumulative confusion matrices. Tables 8 and 9 exhibit the matrices for 3-NN and MLP classifiers, respectively.

Table 8:

Confusion matrix for 3-NN classifier (CA=0.63)

Emotions	neutral	joy	surprise	anger	sadness	fear	disgust
neutral	881	125	2	155	340	48	101
joy	106	922	7	238	115	1	154
surprise	13	1	1135	8	8	390	13
anger	130	151	6	862	81	2	120
sadness	229	130	33	101	823	104	88
fear	41	0	220	5	88	871	4
disgust	76	147	73	107	21	60	996

Table 9:

Confusion matrix for MLP classifier (CA=0.73)

Emotions	neutral	joy	surprise	anger	sadness	fear	disgust
neutral	1160	75	9	29	644	61	41
joy	81	1178	0	57	141	0	129
surprise	3	0	1153	4	2	426	10
anger	58	137	0	1346	44	0	88
sadness	122	13	5	0	561	75	2
fear	8	1	308	1	74	910	2
disgust	44	72	1	39	10	4	1204

Initially, we examine ratings for perceived sincerity and categorization of emotions from human raters. For all photographs as well as for each emotion category, independent t-tests are used to compare the sincerity of non-standardized facial expressions versus standardized facial expressions. As a result, we examine the results of human emotion recognition in order to provide a standard against which FER may be measured. Non-standardized and standardized facial expressions are statistically tested for differences in all emotion categories using independent t-tests. Using one-sample t-tests against zero, we may also infer patterns of incorrect emotion categorization in humans. T-test results are provided using Cohen's d for all t-tests.

Second, we look into how well face detection works in practise. FER is a two-step procedure that begins with the identification of faces and ends with the categorization of facial expressions based on their associated emotions. We measure how often photographs a particular face-detection programme fails to identify a face (dropout rate).

And lastly, in order to describe the performance differences between the three FER tools in terms of several indices of emotion categorization (i.e., accuracy, sensitivity, and precision), we did the following: Evaluation of emotion classification algorithms relies on comparing the output of each algorithm to the original coding of the desired emotional facial expression category (i.e., ground truth). There are a variety of instruments available that may be used to gauge various aspects of emotion. A winner-takes-all principle dictates that the category with the greatest degree of certainty be designated as the winner. The percentage of properly recognized photos out of all images where a face is analyzed is a good indicator of FER performance (thus, excluding drop out) Categories specific sensitivity and accuracy may also be used to assess emotion categorization. Sensitivity is the percentage of accurately predicted photos out of the total number of images in a given category. An evaluation of the tool's ability to identify certain types of data. Perfection is a measure of how many photos projected as a single category are accurately predicted out of all predicted images. It's a measure of how much we can rely on the tool's categorization. We also create confusion matrices for the FER measurement and the genuine categories in order to uncover patterns of categorization.

In the last section, we provide results from ROC analysis and statistical testing of the associated AUC for the three systems and human data to show the differences in emotion recognition performance between them and human data (AUC). An initial two-class classification technique is used in ROC analysis one observation is used in the ROC analysis for classifying data into many categories using the ROC method.

5. CONCLUSION

In our trials, we were able to accurately classify seven different emotional states with a classification accuracy of 96 percent when data were divided randomly and a classification accuracy of 73 percent when data were divided in a "natural" way. The MLP classifier with "natural" data division for all users yielded this result (subject-independent). A user's position with respect to the Kinect was maintained throughout the experiments. We may assume that facial expressions had an impact on the accuracy of the classifications. The categorization accuracy may be impacted by a variety of other circumstances in real life. Depending on the intensity of your emotions, your facial expressions may be more or less visible.

Face expression and auditory emotion classification were examined for their strengths and drawbacks in this study. Certain pairings of emotions are often misclassified in these one-dimensional systems. The findings provided in this research, on the other hand, suggest that a different modality may clear up the majority of these misunderstandings. It was thus more effective than any unimodal emotion classifier in determining a person's emotional state. We contrasted feature-level fusion with decision-level fusion as two types of fusion. Both methods performed equally well in the long run. However, there were considerable variations in the identification rates of various emotions. When compared to the facial expression classifier, which was the best unimodal system, the feature-level bimodal classifier successfully discriminated rage and neutral mood. The decision-level bimodal classifier successfully distinguished between joy and sorrow. For this reason, it is important to choose the optimum fusion method based on the application. The findings of this study demonstrate that it is possible to accurately identify human emotional states using audio and visual modalities. If future human-computer interfaces are able to recognise input from users and react correctly and opportunely to changes in users' emotional states, this might enhance present interfaces' functionality as well as user participation.

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