INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 18, Issue: 4, Month: August, Year: 2023
Article Number: 4644, https://doi.org/10.15837/ijccc.2023.4.4644

CCC Publications

Facial emotion recognition using geometrical features based deep learning techniques

J.L. Mazher Iqbal, M. Senthil Kumar, Geetishree Mishra
Asha G.R., Saritha A.N., A Karthik, BonthuKotaiah N.

J.L Mazher Iqbal
Department of ECE, Veltech Rangarajan Dr sagunthala R&D Institute of Science and Technology
Chennai, India
Corresponding author: mazheriq@gmail.com

M. Senthil Kumar
Department of ECE, Sree Dattha Group of Institutions
Sheriguda, Ibrahimpatnam, Hyderabad, 501510, India

Geetishree Mishra
Department of Electronics, B.M.S College of Engineering
Bull Temple Road Bangalore Karnataka-560019, India

Asha G R
Computer Science & Engineering, B.M.S. College of Engineering
Bangalore, Bull Temple Rd, Basavanagudi, Bengaluru, Karnataka 560019, India

Saritha A N
Computer Science & Engineering, B.M.S. College of Engineering
Bangalore, Bull Temple Rd, Basavanagudi, Bengaluru, Karnataka 560019, India

A Karthik
Institute of aeronautical Engineering, Hyderabad, India

BonthuKotaiah N
Department of Computer Science Central Tribal University of Andhra Pradesh
Vizianagaram, India

Abstract

In recent years, intelligent emotion recognition is active research in computer vision to understand the dynamic communication between machines and humans. As a result, automatic emotion recognition allows the machine to assess and acquire the human emotional state to predict the intents based on the facial expression. Researchers mainly focus on speech features and body motions; identifying affect from facial expressions remains a less explored topic. Hence, this paper proposes a novel approach for intelligent facial emotion recognition using optimal geometrical features from facial landmarks using VGG-19s (FCNN). Here, we utilize Haarcascade to detect the subject face and determine the distance and angle measurements.The entire process is to classify the facial expressions based on extracting relevant features with the normalized angle and distance measures. The experimental analysis shows high accuracy on the MUG dataset of 94.22% and 86.45% on GEMEP datasets, respectively.

Keywords: VGG-19s, Emotion Recognition, Facial Analysis, Facial Landmarks, Feature Extraction, Geometrical features, Hyper parameters

1 Introduction

The field of Artificial Intelligence has a long-term challenge in developing a more leadership. effective leadership for detecting human emotions. Facial emotion recognition (FER) is indeed an essential visual-based technique for creating a more expert system capable of recognizing human emotions. The current methods in FER are based on Action Units (AU), perceptual traits, and geometrical features. AU employs over 7,000 potential AU combinations to differentiate between emotions, which may be highly expensive and increase processing time. Universalizing physical characteristics is another challenging topic [1]. Facial expressions are one of the most reliable markers of a person's mental state. Hence, FER has been used in a variety of fields, such as security, rehabilitation, marketing, & sales. Feature extraction and selection are two primary areas of focus [2] while designing efficient FER systems. The computer vision community as a whole sees emotion identification via facial expression as problematic because of issues including individual diversity in facial structure, the difficulty of distinguishing dynamic facial traits, low quality digital photographs, etc. [3]. As technology has progressed, so too has the use of human face recognition in a variety of contexts. More research into to the user's facial gestures and emotions is necessary for certain HCI initiatives, such as those using a camera-equipped chatbots or a companion robots [4].

Face Emotion Recognition is crucial for human-machine interaction and communication (FER). In order for the computer to understand the user's emotional state and appropriately react, it studies their facial expressions. For many years, researchers have toiled to create facial expression recognition (FER) systems [5]. As people rely mostly on spoken signals and facial photos to comprehend the emotional condition of others, it makes sense to utilise both together. The unique characteristics of speech and visual data make integration a significant obstacle in emotion-recognition studies [6]. Facial expressions provide the brain with the most consistent data for reading human emotions across contexts. Research into emotion recognition has developed at an exponential pace in recent years, and facial expression recognition has emerged as a promising, hot field of study for recognising a broad spectrum of basic emotions. One of the most basic emotions with many applications is joy, and studies have shown that face expressions are more accurate than other approaches (such as audio/speech, text, & physiological sensing) for gauging emotional states. Although most recent methods were developed for recognising a wide range of emotions, improving their detection performance for a particular emotion is a significant challenge (e.g., happiness). There aren't many methods designed to pick out a single happy mood in unrestricted videos, and the ones that do have insufficient accuracy because they don't take into consideration the processing of dramatic changes in head attitude [7]. Emotion recognition, or the study of how well computers can interpret human feelings, is a burgeoning area with several practical applications. The challenge with most approaches to emotion recognition based on visual signals is that individuals may hide their emotions by making subtle changes to their expressions. As human emotions may be hard to pin down using traditional machine learning and deep learning methods, EEG signals are increasingly being used for this purpose. Yet, most of the proposed algorithms have subpar performance. Two convolutional neural network (CNN) approaches are proposed in this study for effective recognition [8]. Model M1 is a fully parameterized CNN, whereas model M2 is a less parameterized CNN. Speech emotion recognition refers to studies in signal processing that attempt to identify feelings based on recordings of people's voices (SER). Because to its widespread application in settings as diverse as mental diagnosis and human-computer interaction, SER necessitates a robust framework for accurate classification. With this goal in mind, we provide a yeast 2 - hybrid deep feature selection (HDFS) method for emotion recognition from human conversations, which combines machine learning with autonomous keyword engineering to achieve state-of-the-art performance in both precision and computational efficiency. The dimensionality reduction process in our pipeline begins with a fuzzy entropy and similarity-based functionality classification algorithm as well as ends with the widespread used Whale optimisation algorithm.

These features were extracted from raw audio signal mel-spectrograms using a qualified Wide-ResNet-50-2 supervised neural model.A k-nearest neighborhood classifier is used to the best collection of features to determine an emotion's category [9]. The ability to recognise human emotions is a huge boon to the field of computer vision. Important for their safety in the case of a meltdown, this is the beginning of an automated service for identifying the feelings of autistic children. Contemporary approaches to a breakdown issue are proactive as opposed to reactive. Meltdown symptoms are sometimes shown by abnormal facial expressions [10] brought on by a mashup of different emotions. Automated emotion recognition is gaining prominence due to the increasing usage of human-computer interface software. Emotion identification may make use of a wide variety of data sources including but not limited to speech, facial movements, body language, & physiological signs. The most trustworthy emotional attachment with machines is established through the physiological indicators that are practically impossible to manipulate. Thus, there's been a lot of research on the challenge of automatically recognising emotions from EEG data. Emotions come from a broad variety of cognitive processes that involve various regions of the brain, making it necessary to recover a large number of features from the whole brain in a number of bands in order to correctly identify them in EEG. When investigating how the brain controls its emotions, it's crucial to account for the ways in which different regions work together [11]. Facial expression recognition (FER) is a challenging yet fascinating area of computer vision (CV). While many academics have devoted significant resources to studying FER in recent years, they perform very well on high-resolution pictures but struggle to discern in the wild between specific emotional states [12].

Face emotion recognition from pictures is challenging since human facial expressions are notoriously hard to predict. Emotion classification using deep learning (DL)-based techniques has not been as successful as the current study. Incorrect layer choice inside the CNN model causes these models to underperform [13]. The ability to express and understand one another's feelings is fundamental to effective communication. Improvements in emotion recognition have a significant impact on both human-computer interaction and computer-based voice emotion identification. Speech emotion recognition (SER) is indeed the practise of determining the emotional state of a speaker based on what they say or what they overhear others say. Hybrid systems have been proven to outperform the more frequent single classifiers used in SER [14], but they are it isn't without their faults. If you can read a player's mood while he's engaged in an interactive game, you may be able to provide him a more rewarding experience. Monitoring the player's intrusive physiological signals is a common practise in current methodologies for evaluating their emotional state [15]. This study proposes a geometric feature-based emotion identification system using a VGG-19s model to identify and classify common emotions such as happiness, sorrow, neutrality, wrath, fear, disgust, and surprise. The subject's face is first identified using a Haar-Cascade classifier, and then geometric facial feature points are extracted from the different regions of the face using this information (such as the eyelids, cheeks, chin, and lips). We can gather the deformations (facial modifications) induced by various expressions by employing the dimensions of the most significant face landmarks to compute the angles and distances between the chosen facial regions, yielding the feature vector. The resulting feature vector is the result of integrating the two. The system uses a VGG-19 architecture and tweaks the DNN's optimal hyperparameters to improve recognition accuracy. Together, these characteristics are what the model learns to utilise to predict the system's robustness. The proposed technique is validated using Geneva Multimodal emotion projections (GEMEP)[13] bodily gesture dataset as well as the Multimedia Comprehension Group (MUG)[12] facial expression database. High levels of recognition accuracy were achieved on both datasets through the application of a VGG-19.

This paper will be organized as follows: Section 2 provides a summary of the existing literature on facial expression recognition. In Section 3, we lay out the suggested methodological framework for designing feature extraction from geometry. In Section 4, we present the experimental setup, performance measures, and results from the MUG and GEMEP databases. The conclusions and suggestions are briefly outlined in Section 5.

2 Related Work

Authors were proposed a novel approach to emotion identification using geometrical fuzzy logic in this research. The four-corner features of the mouth and eyes may be determined even without a reference face. The recovered features specify the quadrilateral shape that did not map to geometric forms. Fuzzy membership functions are used in the proposed Mixed Quadratic Shape Model (MQSM) to quantify the degree to which the quadrilateral is inaccurate. Fuzzy features are extracted from attribute values and used to verify the classifier (12 in total). To test the performance of the MSQM, the CK, JAFFE, & ISED databases are used in the experiment. Using just 12 fuzzy attributes, the proposed method beat state-of-the-art techniques that often depend on reference pictures [16]. Researchers have traditionally used static feature selection methods in their studies. Despite their usefulness, these methods nevertheless have some significant limitations, particularly as they pertain to dealing with spontaneous discourse. This is mostly due to the fact that each person's facial characteristics result in somewhat different emotional expressions. To address this problem, we provide a dynamic attribute selection approach based on facial characteristics, which draws on two types of geometric features: linear features & eccentricity features. When combined, they provide light on why and how our facial expressions look the way they do. The suggested method also considers the subject's head position, muscles, and facial expressions.

The proposed technique outperforms the state-of-the-art methodologies, as shown by experiments performed on the CK+ & DISFA datasets, and maintains its advantage even when evaluated against different datasets. When applied to the CK+ dataset, the proposed method obtains an excellent 97.72% reliability in facial expression identification, while on the DISFA dataset, it gets an impressive 91.26 percent accuracy [17]. We present a convolutional neural network (CNN) that could determine an individual's emotional state from a single image of their face. For the purpose of emotion recognition, the proposed FS-CNN first analyses facial landmarks to anticipate emotions. Hybridization of patch cropped and convolutional neural network technology yields the FS-CNN. In the first stage, we take care of locating faces in high-resolution images and cropping them as needed. In order to anticipate facial expressions using landmarks analytics, we then used a convolutional neural networks (CNN) to pyramid pictures and evaluate scale invariance. Using UMD Faces database, the proposed FS-CNN was evaluated and improved. On average, almost 95% accuracy was attained, which is excellent [18].In this paper, we present our Emotion, Age, and Gender Recognition (EAGR) system, which employs face recognition algorithms to infer a user's emotional state, chronological age, and sexual orientation. The EAGR system uses a

CNN with three training models to identify seven emotions (six basic one and neutral), 4 age groups, as well as two sexes; normalized facial crop rotation (NFC) is tried to apply as a merely helpful preprocess to the training data; and augmented data is then used. The NFC will shave down hair so that facial features may be extracted more easily for use in emotional analysis. Yet, the NFC would be capable of removing facial features, such as age and gender, while the hair remains intact. The experiments made use of the 3-training model for recognizing emotions, ages, and sex. By compensating for subjects' slanted heads in the validation dataset, the proposed binocular line angle correction (BLAC) yielded best-in-class mean average accuracy of 82.4%, 74.95%, & 96.65% for real-time detection of seven moods, four age groups, as well as two genders, respectively. Moreover, NFC preprocessing has the potential to significantly reduce training time. So, we consider the EAGR approach to be cost-effective when trying to determine the gender, age range, or emotional state of a human subject. More accurate feedback based on a wide range of face classifications may be possible thanks to other social uses of the EAGR approach used by HCI services [19].

In order to advance from where we are now, this research proposes a novel FER layout. Improved Black Hole's global search capabilities as well as the Deep Learning Machine's good generalization skills collaborate to sort faces into categories (ELM). Our approach uses Linear Discriminant Analysis (LDA) & Principal Component Analysis (PCA) to reduce the file sizes of facial images while preserving their essential distinguishing features. The suggested technique has shown encouraging results on all three of these datasets, including the Japanese Female Facial Expression (JAFFE), the Karolinska Directed Emotional Faces (KDEF), as well as the expanded Cohn-Kanade (CK+). We also employed our own customized face dataset to further analyses the proposed system, and found that the LDA-BH-ELM approach had an efficiency of 77% just on CK+ dataset & 80% on the KDEF database. Results showed that the proposed technique is better to traditional methods and may provide remarkable performance [20]. In this paper, we provide a method for emotion identification that makes use of both vocal cues and visual cues in tandem with one another. We develop three distinct varieties of VGG-19s. Each of the neural nets is trained to identify emotions from a collection of pictures. Facial landmarks are sent into a second network that may be able to depict facial motions. The audio is converted to its acoustic properties and then used as inputs to the other network, which is responsible for visual synchronization. Using an unique integration technique, we merge these three networks to improve the precision of their emotion recognition findings. As proof of the effectiveness of the suggested approach, a comparison with another technique is provided. The results suggest that this new approach is far better than the previous ones [21]. The Happy Emotion Recognition system presented here improves upon previous work by combining 3D hybrid depth & closeness features with conventional 2D deep features (HappyER-DDF). As a first step towards recovering spatiotemporal information from a picture sequence, we use a 3D Original conception artificial neural hybrid having long-short term memory (LSTM). Second, when a grin unfolds, we quantify the space occupied by various facial features relative to an external point of reference (such as the nose peak) (or laugh). We use three publicly available video datasets to assess functional & decision-level fusion techniques. Our HappyER-DDF approach outperforms state-of-the-art facial expression technology [22] in terms of accuracy, as shown by the findings. Being the most widely used EEG reference dataset, we use the DEAP and its valence and arousal indicators for binary classification in this study. The dataset is complete with the addition of frequency domain Fast Fourier Transform (FFT) extraction of features to supplement convolutional feature extraction. When compared to other models, the M1 and M2 CNN designs achieve average accuracy of 99.89% & 99.22%, respectively. We demonstrate the M2 model's ability to consistently categorise polarities including over 96% accuracy using just 125 ms of EEG inputs and EEG outputs, and to reach 99.22% accuracy using only 2 seconds of EEG outputs. Our suggested M2 model achieves a valence accuracy of over 96.8% with just 10% of a training dataset. The source code used to carry out each experiment is made publicly available with its description [23].

Using a 5-fold cross-validation approach, we evaluate the suggested pipeline against a wide range of state-of-the-art, recently published studies and find that it greatly outperforms them, demonstrating the excellence and reliability of our work [24]. This essay painstakingly created the geometric, spatiotemporal, and profound features of autistic children's face expressions. In order to accomplish this, we compared the performance of various combinations of these factors in Complex Emotion Recognition (CER) and determined which features are most useful in identifying a Complex Emotion (CE) in autistic children during a crisis breakdown from a typically functioning state. The "Meltdown crisis" 1 dataset, which details real-world Meltdown / Normal scenarios involving autistic youngsters, was used to verify our assumptions. We show that the given data may provide exceptionally promising results using a Random Forest classifier (91.27%) using custom-built features. Classifiers trained on feature representation using InceptionResnetV2 utilising supervised learning approaches provide state-of-the-art results (97.5% accuracy) [25]. In this study, 736 features are extracted from spectral power and phase-locking data. To solve the challenge of learning key characteristics for emotion recognition, we use swarm-intelligence (SI) algorithms here. We were able to apply the feature sets selected by these classification approaches to the problem of distinguishing between happy and sad facial expressions.

In addition, popular features are often recycled into an updated feature set. Using the random forest classification technique, we found an accuracy between 56.27 and 60.29 percent. The improvement was possible because to an 87.17 percent reduction in file size, from 736 features to 94.40 features. We also highlight the importance of focusing on the best electrode locations for reading emotions. The categorization findings [26] are promising, and we conclude that 11 channels predominate.To solve this issue, we created three novel applications of neural networks. In this instance, we employed multi-scale kernel architectures with incorporated asymmetric pyramidal networks (APNet). The square kernel was also replaced with a set of convolution layers in the x, y, and z directions. This approach may enhance CNNs' descriptive power by making it simpler for them to integrate multi-scale information across their many layers. Utilizing random gradient descent and gradient centralization during CNN training led to significant improvements (SGDGC). To verify the effectiveness of APNet with SGDGC, experiments were performed on the widely used FER-2013, CK+, and JAFFE emotional datasets. The results of our trials & compared to other government models [27] demonstrate that our method is superior than utilising a single model and is on par with the outcomes achieved to use a model fusion strategy. We present a powerful DL solution for this issue by classifying facial expressions according to their emotional content using the CNN structure. In this study, we show how to analyse Viola-Jones (VJ) facial detector output in a novel way by using a more advanced network architecture. After extensive testing to determine the optimal arrangement, An first layer of the proposed model was developed. Many subjective and objective indicators of performance informed our final verdict. The results not only show that people feel different things, but also that those feelings may vary in strength. We conduct experiments on the fer-2013, ck+, & kdef datasets to test the proposed model and compare the results to those obtained using state-of-the-art methods. Research like this has the potential to aid authorities in "smart urban" [28].

The purpose of this research was to examine a suggested hybrid Long Short-Term Memory (LSTM) Networks using Transformational Encoder in order to classify speakers' emotions and make sense of their voice signals. Mel Frequency Cepstral Coefficient-derived speech characteristics are used in the suggested fusion method for the categorization of long-term memories (MFCC). The LSTM-Transformer model's performance was evaluated using rigorous testing. The results show that this is a significant improvement over the reported models before it. Recognition accuracy for the proposed hybrid model was 75.6% just on RAVDESS dataset, 85.5% on the Emo-DB dataset alone, and 72.4% just on vernacular dataset [29]. We found that HR and facial expressions may be used to infer a player's emotional state, and we provided a mechanism for doing so (FE). Because of the fleeting nature of people's emotional reactions, this research uses Kinect2.0 video for HR and FE detection in real time. A convolutional neural network (CNN) is used to train the FE features, while a network with both long and short-term memory (Bi-LSTM) is used to learn the HR features. Accurate emotion identification is achieved by the SOM-BP networks by combining HR and FE characteristics. Our experimental results demonstrate that our model is capable of accurately predicting players' levels of joy, rage, sorrow, and composure in a large set of games with low computational requirements. In light of this, the HR value may be a measure of how strongly you feel [30].

From what has been said, it is clear that methods have been developed to determine emotional states based on visual data & body language signals generated from dynamic aspects. Although while the problem is less severe with still images of faces, there are still some emotions that can be differentiated. To identify an emotion, it is sufficient to have at least some of the face traits present in a given image. By zeroing down on a few important features, we can often determine the underlying emotional expression. So, we refined our framework to focus on 66 variables representing more complex face regions by including the geometric measure. Choosing appropriate hyper-parameters is the most difficult component of constructing a model utilizing deep learning. We tested the model's prediction ability under a variety of parameter combinations over tight ranges.

3 Proposed Approach

The proposed framework is shown in Figure 1. It consists of three stages (i)Facial Localization and Landmark points detection,(ii)Facial geometric feature extraction using VGG-19, and (iii) Emotion Classification using FCNN. We analyse the facial databases like MUG and GEMEP where a single face appears in eachvideo/image frame for this work. Initially, the subject's face is extracted from the facial input image sequence and 68 landmark points were identified from the faceregion. Following that, a geometrical face feature extraction is made with the distance and angle measures.Finally,the extracted features are given to FCNN for training and testing the facial emotions from the MUG and the GEMEP dataset.

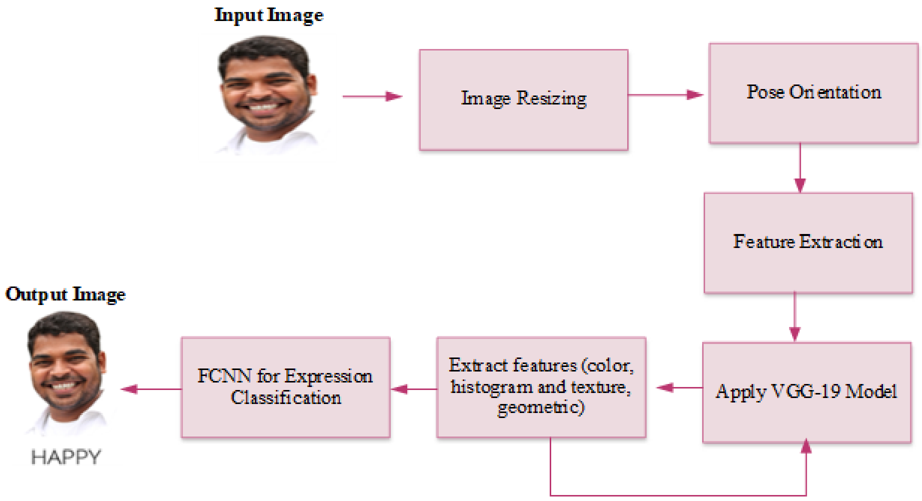

Figure 1: The frame work of the proposed system

3.1 Facial Localization and Landmark Detection

This session initially extracts the facial region of interest (ROI) from the input image/video. For better recognition of face emotion, we used OpenCV's built-in Haarcascades to locate the face in the image.It improves the trade-off performance -Jones(VJ)algorithm for face detection [14], a dynamic approach used to detect the object with a cascade function.Face detection is achieved easily by training the classifier with a set of positive and negative frames by the AdaBoost algorithm and modifying the extracted weight features.Faciall and mark identification is vital in many face analys is tasks to articulate specific facial behaviours based on facial muscle movements. Figure 2shows the cropped face ROI and selected to analyse the temporal information byidentifying the 68 landmark points using the Dlib frontal face detector toolkit [34].Facial expression recognition begins with accurate and significant extraction of facial landmark features from the eyes,nose,eye brows,and lips.

Figure 2: Face Localization and Landmark Detection

3.2 Facial Geometrical Feature Extraction

Following the motions of prominent points inside the head, eye, eyebrows, nose, tongue, lips, and jaw, a geometrical feature-based technique may extract minute changes in facial shape and movement. So, we considered the feature representation based on the distance & angles of facial feature points in this investigation to differentiate between emotions. By suggesting angle points and Euclidean distance between each pair of markers in a frame, FACS defines features. In total, 66-dimensional features were taken from the facial information points, representing 47 unique Euclidean distances and 19 angl emeasures between the coordinates of facial landmarks. As a result, only the mostperilous facial features are added, as other distances points have only aminor effecton a classifier's decision-making. Figure 3 (a) and (b) shows the geometrical landmark points for distance and angle measure.

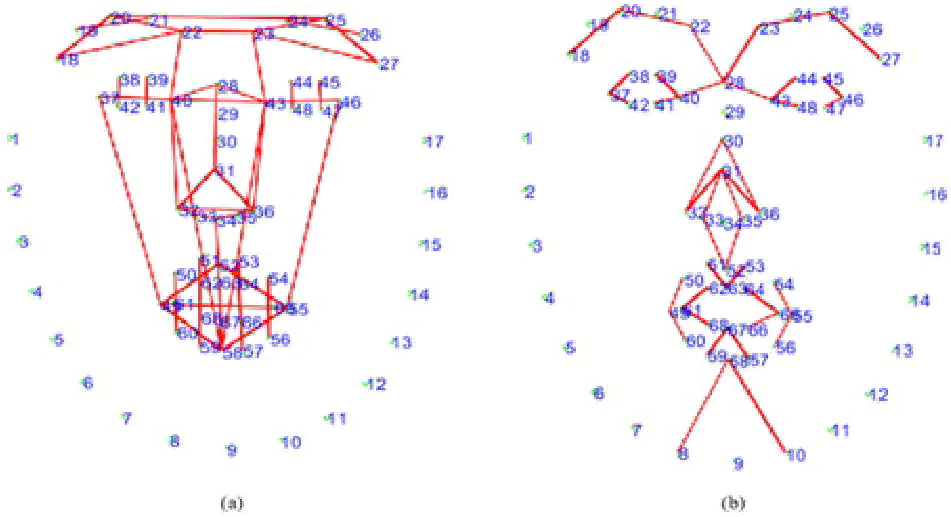

Figure 3: Facial Geo metrical Points (a) Forty-Seven Landmarks points selected for Distance measure(b) Nineteen Landmark points selected for Angle measure

Using the use of Pythagoras' Theorem, we may estimate the distance and angle between two points on a face by utilising the points as landmarks. The distances between the various features of the face are denoted by the pairs (xi, yi). 66-dimensional feature points are used to calculate point indices because of their high sensitivity to subtleties of facial expression. Pairwise measurements of a two landmarks may be used to extract features for FER. The 47 distance characteristics as well as the 19 angle characteristics, each with its own id, are listed in Table 1. Before estimating the angles between the three sets of points, we calculate the distance among each set of landmark coordinates inside a frame. Second, in order to train VGG-19s, feature fusion utilises a combination of cartesian angles and distances between points to distinguish between 66 distinct facial expressions, ranging from "neutral" to "extreme". object. The robot as well as the faces/emotions are separated by the length (in x and y axes). Face emotion recognition rely on four coordinates (x, y, w, and h) in the frame: Bounding boxes are denoted by x and y in the coordinate system; w and h represent the height and breadth of the a bounding box, as well as the final values of w and h are used to determine kdX and kdY. The x and y dimensions are calculated as follows:

$$kdX = \frac{StartX+En}{2}$$

$$kdY = \frac{StartYY+EndY}{2}$$

wherein kdX is the x coordinate, kdY is the y group up, Start X is the beginning of the X axis in the structuring element, Start Y is the beginning of a Y axis inside the structuring element, End X is the end of a X-axis as in bounding box, & End Y is the end of the Y-axis inside the bounding box. Moreover, the robot's built-in camera's distance from the detected face is determined by the formula:

$$\text{"focal length "} = \frac{wxd}{W}$$

$$\text{"distance "} = \frac{Wxf}{W}$$

3.3 Statistical Feature Analysis

The box plot indicates the variance of individual class instances for representing facial emotion recognition. Figure 4 and 5 represents the feature distribution of the distance angle measures in a statistical box plot analysis for MUG and GEMEP datasets. Each discrete box in the box plot signifies the emotional class instance; the central red line in the box maps the median of the sample data. The whiskers at the top and bottom of the box indicate extreme data points without outliers, plus symbols outside the box mark the outlier features. As a result, these plots show the variant features accurately discriminating the emotions of MUG and GEMEP datasets.

Table 1.Facial Geometric points for Distance and Angle measure for feature extraction.

Facial Geometric Features					
Distance				Angle	
#ID	Dist.	#ID	Dist.	#ID	θ
D1	pt18, pt22	D25	pt34, pt52	A1	pt18,pt20, pt22
D2	pt19, pt21	D26	pt49, pt55	A2	pt23,pt25, pt27
D3	pt18, pt20	D27	pt52, pt58	A3	pt38,pt37, pt42
D4	pt20, pt22	D28	pt49, pt52	A4	pt39,pt40, pt41
D5	pt23, pt27	D29	pt52, pt55	A5	pt44,pt43, pt48
D6	pt24, pt26	D30	pt49, pt58	A6	pt45,pt46, pt47
D7	pt23, pt25	D31	pt58, pt55	A7	pt32,pt31, pt36
D8	pt25, pt27	D32	pt37, pt49	A8	pt33,pt31, pt35
D9	pt20, pt25	D33	pt46, pt55	A9	pt40,pt28, pt43
D10	pt22, pt23	D34	pt40, pt28	A10	pt32,pt30, pt36
D11	pt22, pt40	D35	pt43, pt28	A11	pt51,pt63, pt53
D12	pt23, pt43	D36	pt31, pt28	A12	pt59, pt67, pt57
D13	pt37, pt40	D37	pt32 ,pt34	A13	pt50, pt49, pt60
D14	pt38, pt42	D38	pt36, pt34	A14	pt62,pt61, pt68
D15	pt39, pt41	D39	pt62, pt68	A15	pt54,pt55, pt56
D16	pt43, pt46	D40	pt63, pt67	A16	pt64,pt65, pt66

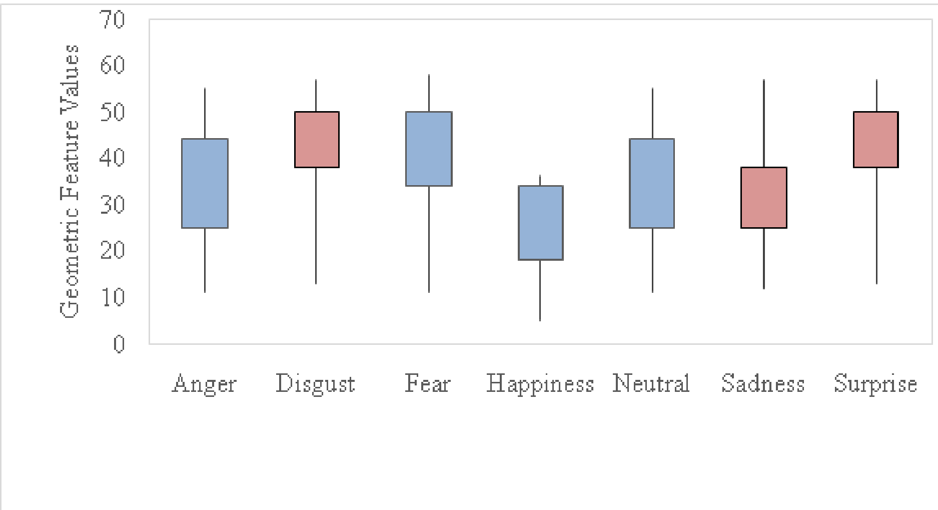

Figure 4: Distance+Angle features distribution on MUG dataset

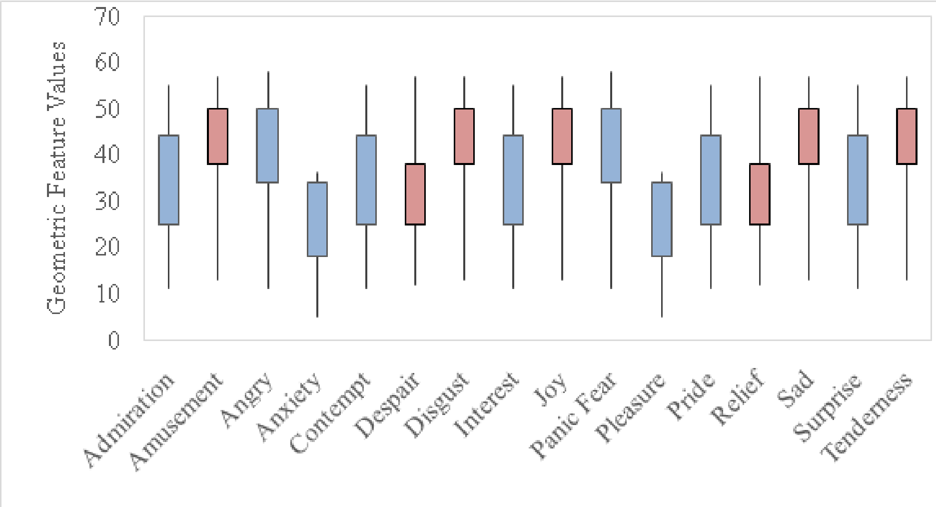

Figure 5. Distance+Angle features distribution on GEMEP dataset

3.4 VGG-19s and FCNN

A. VGG

More than a million images from the ImageNet database were used to train the convolutional neural network (CNN) designated as VGG-19. The network has 19 layers and can divide images into a thousand distinct categories, such as "computer," "mouse," "pencil," and "animal." Because of this, the network can now learn elaborate feature representations for many kinds of images. Yet, despite the fact that the VGG net's primary objective was to triumph in the ILSVRC competition, it has been put to use in a wide variety of different contexts.

• Used simply as a decent classification architecture for a large number of additional datasets, and since the authors made the models accessible to the public, they may be used as is or modified for use in other tasks that are analogous, as well.

• Transfer learning: this method may also be used to problems involving face recognition.

• Weights are readily accessible with other platforms such as keras, which means that they may be manipulated and utilized for any purpose the user desires.

• Loss of both content and format while utilizing the VGG-19 networking VGG-19 Architecture

• A square (224x224) RGB image was used as input to these networks, indicating that the input matrix was also square (224,224,3).

• What has been done in the way of preprocessing thus far is to remove the training set's mean RGB value from each pixel. Just this one action was taken.

• To cover the entire picture, they used kernels that have been three pixel by three pixels and had a stride length of one pixel.

• In order to keep the image's resolution satellite consistent, spatial padding was used.

• sride 2 was used as the technique for maximum pooling across a 2-by-2-pixel window.

• To further enhance the model's classification performance and shorten the calculation time, it was chosen to use non-linearity using Rectified linear unit (ReLu). As compared to previous models that relied on tanh or sigmoid curves, this one was proven to be far better.

• The incorporation of three fully connected layers, the first two of it has a size of 4096, the third of which had 1000 channels for 1000-way ILSVRC classification, and the last of which employed a softmax function.

B. CNN

The Convolutional Neural Network (CNN) is a specific a kind deep neural network framework used in the analysis of visual information. In contrast to traditional image processing, CNN may employ learnt filters rather than edge, histogram, texture, etc. filters. This eliminates the need to learn through making mistakes.

• CNN begins with a feature-learning phase, and it is followed by a classification layer (also known as Fully Connected Layer). Two of the most fundamental building blocks of the feature learning phase are the convolution operation as well as the pooling layer.

• A Convolution Layer is comprised of the Learnable Filters and Feature Extractors that were previously discussed.

• Pooling Layer: This not only brings approximately invariance but also accomplishes some spatial compression. Even if it is turned slightly, an automobile will still be recognizable as such.

C. VGG-19 & FCNN

VGG-19 is a state-of-the-art CNN with or before layers as well as a deep comprehension of the properties of shapes, colours, and structures. VGG-19 is a deep neural network which was taught on millions of pictures of varying types and complexity.

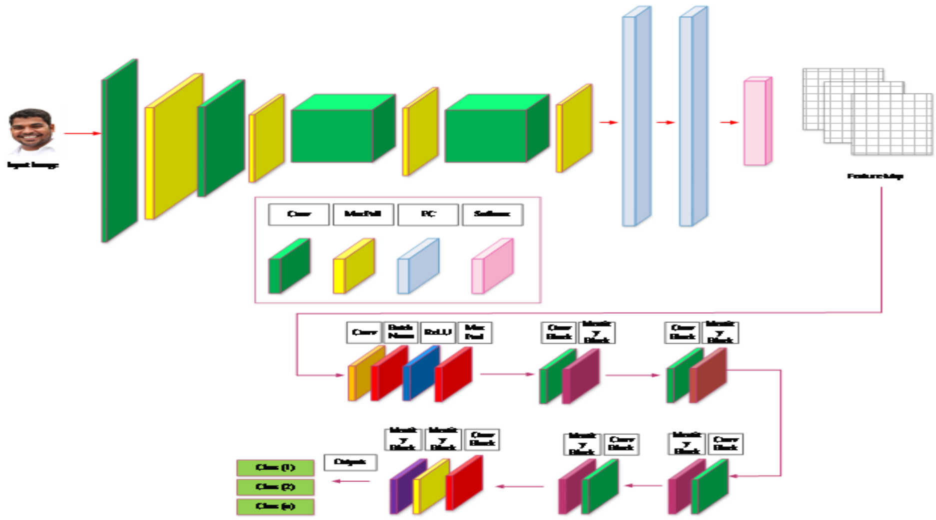

Figure 6: Hybrid Architecture

To complete my classification goal of differentiating between photos with and without trees, we did not further train VGG-19, instead freezing its layers and adding a shallow 2-layer networks on top of it. When f is the characteristic length, w is indeed the width in pixel, d is the length in cm, & W is the widths in cm, the distance is measured to determine the location of an object in addition to facial & emotion identification. When comparing two faces, it's crucial to know their exact x, y, and distance from one another. The challenge with training neural learning is that it takes a lot of information. Because of its large size, the noisy dataset is used for adaptive optimisation, even though our goal is to improve performance just on curated dataset. We minimise the following bridge error during training:

$$\mathrm{L(S,L)}{=}-\sum_{i\varepsilon N} L_i log(s_i)$$

The proposed CNN based attention model comprised of 5 convolutional layers in which the first layer is responsible for extraction of low level features from the input images. The other layers concentrate on the region of interest provided by the FCN-perinet model. The detection of semantic regions was performed by using the FCN and the classification of regions was carried out into three classes namely eyebrow, background, and eye from which the region of interest is constructed. The operation of the attention layer was formulated as, Where $f_{(}p,q)$denotes the feature map of the CNN at the coordinates of the ROI, $f_{(}p,q)^*$ denotes the treated feature map at the end of the current layer and β denote the control coefficient which controls the adjustment intensity. More precisely, let indicate the last convolutional layer's vectorized FCNN answers (e.g. the '$conv5_4$' of VGG19), where m is the total amount of convolutional kernels in the final layer (e.g. m=512 in VGG19), grows linearly with size of the input picture, & d is the amount of nodes each convolutional kernel.

4 Experimental setup

We'll be working within the constraints outlined here. An Intel i7 processor @ 2.10 GHz & 16 GB of RAM are all that's needed for the testing on a Windows 10 machine. The bare minimum for running the VGG-19 and FCNN model is Python 3.76, the Keras 2.4.3 framework, as well as the Tensor Flow 2.3.1 libraries. We experimented with a number of different model setups before settling on one that solved our issue. Unsuccessful model configurations attempted to train the network to recognise novel illustration-domain picture properties. We experimented with retraining the weights of the network's lower layers to pick up on the rudimentary features of the new domain, blocking updates to the network's upper layers to preserve the refined object representation learned during previous training, expanding the network's depth, and tweaking parameters like drop - outs, learning rate, and momentum. One of the most challenging aspects of building VGG-19 models is choosing the combinations of hyper parameters using a looping strategy to increase the accuracy and efficiency of the model. Deep learning with a grid search approach helps in selecting the suitable parameters for obtaining the best prediction model which avoids over fitting. Our VGG-19 consists of five-layered architecture for training andtesting. To assess the performance of our model, we trained our deep architecture up to 25layers,but there is a significan tdecline in the accuracy.As a result,we choose the architecture with minimal layers, which provides significantly faster inference and is moreappropriate for real-time applications.We demonstrate that VGG19's deep network produces much worse accuracy in our illustration database compared to natural pictures. The primary difference between our datasets and the original photos is in their statistical makeup. The creation and training of a brand-new convolutional network is one strategy for enhancing performance on our data. We don't have enough data to train VGG19, as well as erasing the model's previous training would mean losing all of its previous learnings, therefore this is not a wise choice.

5 Dataset

In this study, we analyze facial expression datasets to extract geometrical characteristics, focusing on cases when a single face looks in each picture or video frame. The data comes from two different sources: (a) the MUG and (b) the GEMEP. Table 3 provides a concise summary of the characteristics shared by these two data sets.

Table 3.Facial Expression Datasets

Datasets	Total Samples	Subject	Classes	Temporality	Resolution
Understanding Group (MUG) [12]	11758	86	7	static	896×896
Geneva Multimodal Emotion Portrayals (GEMEP) [13]	1823	10	17	dynamic	720×576
Understanding Group (MUG) [12]	11758	86	7	static	896×896

Multimedia Understanding Group(MUG)
There are seven core emotion prototypes specified in the FACS handbook, and they are all part of the Multimedia Understanding Team facial expression dataset. The dataset consists of 1462 face sequences including various action components from 86 people, including 35 girls and 51 men between the ages of 20 and 35. Preprocessed sequences yielded a total of (11758) pictures.

Figure 7:Sample frames of seven emotions from the MUG dataset.

Portrays seven different facial emotional class instances consisting of angry, disgust,fear, happiness, neutral, sad and surprise. The recorded frames are posed at 19 frames persecond. Furthermore, this datasetis chosen because of its authentic expressions that defeat the limitations of other similar datasets in FER, such as illumination factors and numeroustakes per subject without occlusion.Table 4 depicts the numberof instances perfacial expression.

Table 4.The number of instances taken per facial expression.

Facial Expression	**Instances**
Angry	1587
Disgust	1606
Fear	1638
Happy	1868
Sad	1802
Neutral	1389
Surprise	1868
Total	11758

5.1 GEMEP Dataset

The Geneva Multi-modal Emotion Portrayals(GEMEP)[37]is a multi modal framework created by Klaus Scherer and Tanja Banziger. It consists of facial, audio and bodygesture video instances performed by ten actors with different modalities. It encompasses a wide range of feelings, including: awe, amazement, anxiety, anger, disdain, disgust, desperation, fear, irritation, curiosity, joy, pleasure, pleasure, relief, sorrow, surprise, and tenderness. Initially, thevideo portrayals are converted to frames, with Haar cascade the face ROI is cropped and used for our work.Figure 8 shows the sample frames of the face extraction process from the GEMEP Dataset.For our experiment's studies,1823 instances are considered.Table 5 shows the occurrence of each instance perfacial expression.

Table 5. The number of instances taken per facial expression

Facial Expression	**Instances**
Admiration	127
Angry	105
Contempt	61
Despair	126
Disgust	56
Interest	138
Irritation	134
Joy	113
Panic fear	115
Pleasure	179
Pride	93
Relief	116
Sad	125
Surprise	53
Tenderness	69
Total	1823

5.2 PerformanceMeasures

In this part, we give a metric for evaluating the deep networks model's training-phase performance on the test set. By doing so, we can better understand how quickly the model is able to converge. There is a 70% training and 30% testing split for the suggested retrieved geometrical characteristics. Accuracy (A), Precise (P), Recall (R), F1score, and ROC (Receiver Operating Characteristics) are some of the statistical measures used to evaluate a model's efficacy. Each occurrence of an emotional class in the MUG & GEMEP datasets was evaluated using the metrics presented in Table 6.The effectiveness of the created facial expression recognition system is measured via evaluation. The suggested system's performance is evaluated in terms of its accuracy, which is the rate at which it can recognise faces and expressions in real time. The formula for determining the test's precision is provided (1):

$$\text{"accuracy "} = \frac{TP+TN}{TP+FP+FN+TN}$$

where TP indicates positive results, TN negative results, FP positive results, and TN negative results. This equation is used to achieve high quality in either face recognition or emotions recognition. The accuracy value of a classification reveals its efficiency on a class-by-class basis.

Table 6.PerformanceMeasure

Metric	Description
Accurateness	It measures how many samples were accurately labelled in comparison to the total sample count.
Exactitude	Using the sum of the positive samples, it extrapolates the expected positive ones.
Recollection	It quantifies the proportion of correctly identified emotions.
F-score	F-measure calculates an appropriate performance index by averaging the results of two other metrics, "precision" and "recall".

In this case, we have a four-way dichotomy denoted by the letters TP, TN, FP, and FN.

5.3 Experimental Results on MUG Dataset

Adamax optimizer was used to train for 100 epochs at a training rate of 0.001 to extract distance & angle characteristics from the MUG dataset. For optimal network performance, they utilize Rectified Linear Unit (ReLu) activation functions for all units in the hidden layer and'sigmoid' activation functions for the output layer.

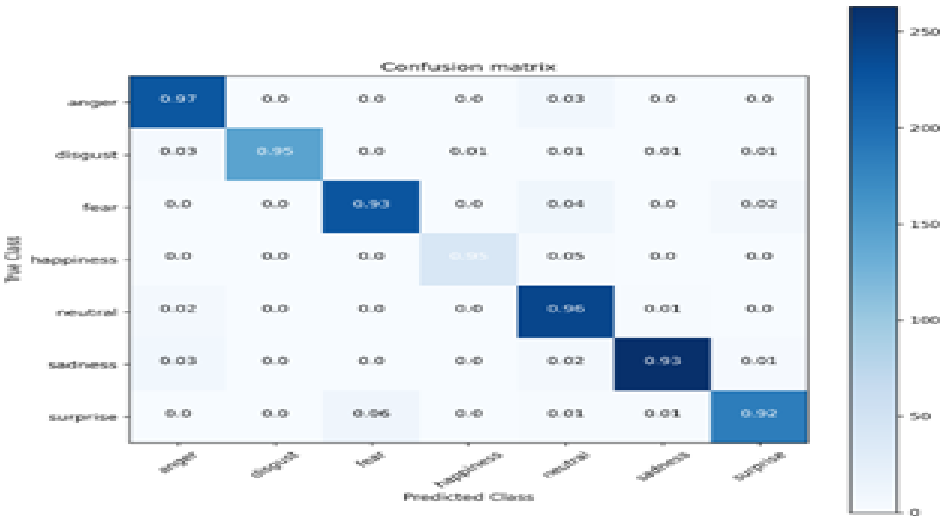

Figure 8:Confusion Matrix:66features employed from MUG Dataset

The confusion matrix of the proposed distance and angle features on the MUG datasetdisplays that 'angry', 'sad', 'happy' and 'disgust' have been classified correctly with the bestaccuracy, and "surprise" has the lower accuracy because some of the emotions like fear are mis classified as a surprise as shown in Figure9.

Table 7 denotes the performance measure of Accuracy, Precision, Recall, and F1-Score values for the DNN model on the MUG dataset. The train and test set's performance accuracy and loss graph produced outstanding results with remarkably high consistency. Asshown in Figure 10 (a) and (b) recognizing facial emotions with 66 landmark features directly correlates to 100 epochs. The validation and train data began to converge at the 60th epoch and remained completely stable,and the system classifies emotion with the accuracy of 94.2 % for the MUG dataset.

6 Experimental Results on GEMEP Dataset

A 100 epoch deep artificial neural model is used to train and evaluate the distance-and-angle fused features from the GEMEP frames. To achieve optimal performance, we employ Rectified Linear Units (ReLu) inside the hidden layer and'sigmoid' in the output layer. When starting with a tiny dataset like GEMEP, dropout and regularisation may help you train the best possible models for the validation set. For example, the confusion matrix for the suggested features just on GEMEP dataset shows that the emotions of "pleasure," "sadness," "irritation," "disgust," "contempt," and "amusement" are accurately categorised. Figure 12 shows that although the category "anxiety" has the highest accuracy, the category "pride" has the lowest accuracy.

Table 7.The performance measure for the MUG dataset

Emotions	Accurateness	Exactitude	Recollection	f1 score
annoyed	0.97	0.92	0.97	0.94
revulsion	0.95	0.99	0.95	0.97
anxiety	0.93	0.95	0.93	0.94
joyful	0.95	0.93	0.95	0.94
unhappy	0.96	0.89	0.96	0.92
neutral	0.93	0.98	0.93	0.95
surprise	0.92	0.95	0.92	0.93

Table 7 denotes the performance measure of Accuracy, Precision, Recall, and F1-Score values for the DNN model on the MUG dataset. The train and test set's performance accuracy and loss graph produced outstanding results with remarkably high consistency. Asshown in Figure 10 (a) and (b) recognizing facial emotions with 66 landmark features directlycorrelates to 100 epochs. The validation and train data began to converge at the 60th epoch and remained completely stable,and the system classifiese motion with the accuracy of 94.2 %forthe MUGdataset.

6.1 Experimental Results on GEME PDataset

A 100-epoch deep artificial neural model is used to train and evaluate the distance-and-angle fused features from the GEMEP frames. To achieve optimal performance, we employ Rectified Linear Units (ReLu) inside the hidden layer and'sigmoid' in the output layer. When starting with a tiny dataset like GEMEP, dropout and regularisation may help you train the best possible models for the validation set. For example, the confusion matrix for the suggested features just on GEMEP dataset shows that the emotions of "pleasure," "sadness," "irritation," "disgust," "contempt," and "amusement" are accurately categorised.

Figure 12 shows that although the category "anxiety" has the highest accuracy, the category "pride" has the lowest accuracy.

Table 8. The performance measure for the GEMEP dataset

Emotions	Accurateness	Exactitude	Recollection	f1 score
Approbation	0.89	0.79	0.89	0.84
Delight	0.89	0.9	0.89	0.89
Annoyed	0.82	0.93	0.82	0.88
Nervousness	0.77	0.87	0.77	0.82
Disdain	0.90	0.87	0.9	0.89
Misery	0.83	0.76	0.83	0.79
Revulsion	0.88	0.84	0.88	0.86
Attention	0.83	0.93	0.83	0.88
Annoyance	0.95	0.89	0.95	0.92
Happiness	0.86	0.82	0.86	0.84
Fright fear	0.77	0.79	0.77	0.78
Favorite	0.94	0.93	0.94	0.94
Arrogance	0.71	0.89	0.71	0.79
Release	0.85	0.79	0.85	0.82
Unhappy	0.94	0.89	0.94	0.92
Amazement	0.84	0.83	0.94	0.88
Sensitivity	0.87	0.9	0.87	0.88

Table 8 displays the results of the performance analysis based on the confusion matrix reliability ratings. According to this table, the suggested model achieves the maximum precision, reliability, recall, and f1 measure as well as requires less computing time when the performance measure is increased for the specified input size.

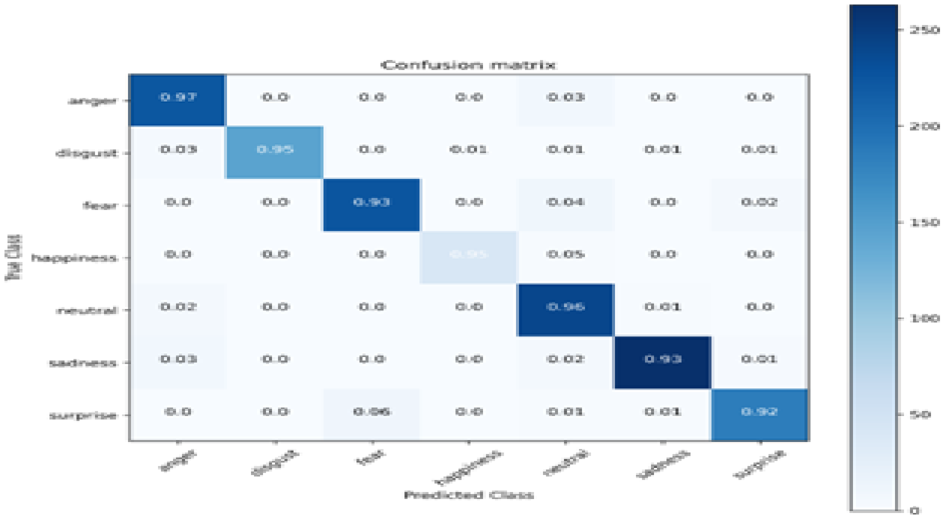

Figure 9:Confusion Matrix obtained for GEMEP Dataset

5. Comparative Study Table 9 contrasts the results provided with those obtained by the state-of-the-art methods, showing that the proposed method for extracting geometrical features is both efficient and effective.

Table 9.State-of-the-artresults

Method	Dataset	Accuracy
ResNet 50	GEMEP	85.6
CNN		87.65
Mobile Net		89.2
Distance Manifolds using SVM		92.76
Geometric features using DNN		94.2
ResNet 50	MUG	84.6
CNN		88.65
Mobile Net		88.2
Distance Manifolds using SVM		91.76
Geometric features usingDNN		95.2

7 Conclusion and Future Work

In this paper, we proposed a new framework for recognizing facial emotion usingVGG-19s. We believe that focusing on specific action units in the facialregionshelpsdetectfacial expressionsin depth.Additionally,weextracted thefacefeature information using euclidean distance and angle measure using 66 distinct facialaction units to highlight the most crucial parts for detecting facial emotions. To train the classifier from beginning and directly forecast the output for the production of input characteristics, it is helpful to construct a VGG-19. Both the MUG & GEMEP databases were used in experiments that sought to isolate individual feelings. Overall recognition accuracy was found to be 94.22% for the MUG dataset and 86.45% for GEMEP dataset. Quantitative measurements including as accuracy, precision, recall, f1-score, and ROC are used to verify the dataset's performance. Lastly, additional techniques developed in the area of face expression identification were compared with the methodologies given in this study. The results indicated that the system was not capable of making a reliable distinction between shock and satisfaction. For a given amount of input, the suggested task requires less time on the computer and produces better performance metrics. Using real-time datasets, we combine face traits with visual body motions to identify micro expressions of emotion.

Declaration:

Participation Consent and Ethical Approval:

This procedure is carried out without the involvement of people. Rights of Humans and Animals:

Animal and human rights are not being violated in any way.

Backing:

There is no money associated with this effort.

Competing Interests:
There is no potential for a conflict of interest with this project.
Contributions to the Authorship:
There is no evidence of authorship.
Salutation:
No credit is due for this creation.

References

[1] Pérez, Ramses Fuentes, et al. "Prototype of MANET Network with Ring Topology for Mobile Devices." (2021).

[2] Rajathi L.V. and RubaSoundar K. -. "A Survey on Various MANET Protocols." International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (2022): n. pag.

[3] Malik, Kamal, and AnshuBhasin. "A survey of mitigation techniques of packet drop attacks in MANET." SSRN Electronic Journal (2022):

[4] Korir, FridahChepkemoi, and Wilson Cheruiyot. "A survey on security challenges in the current MANET routing protocols." Global Journal of Engineering and Technology Advances (2022):

[5] Mohamed, Hossam El-Din, et al. "Using MANET in IoT Healthcare Applications: A Survey." (2021).

[6] Al-Shakarchi, Sanaa J. H. and RaaidAlubady. "A Survey of Selfish Nodes Detection in MANET: Solutions and Opportunities of Research." 2021 1st Babylon International Conference on Information Technology and Science (BICITS) (2021): 178-184.

[7] Alam, Tanweer and Mohamed Benaida. "The Role of Cloud-MANET Framework in the Internet of Things (IoT)." Computational Materials Science eJournal (2018): n. pag.

[8] Lakshmi, G. Vidhya and P. Vaishnavi. "An Efficient Security Framework for Trusted and Secure Routing in MANET: A Comprehensive Solution." Wireless Personal Communications 124 (2022): 333 - 348.

[9] Jabbar, Waheb A. et al. "MEQSA-OLSRv2: A Multicriteria-Based Hybrid Multipath Protocol for Energy-Efficient and QoS-Aware Data Routing in MANET-WSN Convergence Scenarios of IoT." IEEE Access 6 (2018): 76546-76572.

[10] Serhani, Abdellatif, et al. "AQ-Routing: mobility-, a stability-aware adaptive routing protocol for data routing in MANET–IoT systems." Cluster Computing 23 (2019): 13-27.

[11] Gomathi, K. and B. Parvathavarthini. "A Secure Clustering in MANET through Direct Trust Evaluation Technique." 2015 International Conference on Cloud Computing (ICCC) (2015): 1-6.

[12] Piyalikar et al. "Forecast Weighted Clustering in MANET." Procedia Computer Science 89 (2016): 253-260.

[13] Suma, R., and Suma. "Integration of particle swarm optimization with an adaptive K-Nearest Neighbor for energy-efficient clustering in MANET." (2020).

[14] "A HYBRID APPROACH FOR NODE CO-OPERATION BASED CLUSTERING IN MANET." (2018). Krishnan, Rahul. "A Survey on Game Theory Approaches for Improving Security in MANET." (2018).

[15] Gupta, Alok and Nikhil Ranjan. "A Survey of Attacker Identification and Security Schemes in MANET." (2020).

[16] Muruganandam, S. et al. "A Survey: Comparative study of security methods and trust manage solutions in MANET." 2019 Fifth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) 1 (2019): 125-131.

[17] Usha, G. et al. "Survey of Single and Cross Layer Security in MANET." Indian journal of science and technology 9 (2016):

[18] Sumra, Dr.Irshad Ahmed, et al. "Security issues and Challenges in MANET-VANET-FANET: A Survey." EAI Endorsed Transactions on Energy Web 5 (2018): 155884.

[19] Rao, A. Arjuna et al. "Survey of Routing Protocols and Routing Attacks in MANET with Different Security Technique in Cryptography for Network Security." (2018).

[20] Poongodi, M. et al. "5G based Blockchain network for authentic and ethical keyword search engine." IET Commun. 16 (2021): 442-448.

[21] Zhang, Lei et al. "How Much Communication Resource is Needed to Run a Wireless Blockchain Network?" IEEE Network 36 (2021): 128-135

[22] Nikhade, Jitendra R. and Vilas M. Thakare. "BlockChain Based Security Enhancement in MANET with the Improvisation of QoS Elicited from Network Integrity and Reliance Management." Ad Hoc Sens. Wirel. Networks 52 (2022): 123-171.

[23] Suma, R. and Suma.. "Integration of particle swarm optimization with an adaptive K-Nearest Neighbor for energy-efficient clustering in MANET." (2020).

[24] J, Martin Sahayaraj et al. "IEEHR: Improved Energy Efficient Honeycomb based Routing in MANET for Improving Network Performance and Longevity." International Journal on Recent and Innovation Trends in Computing and Communication (2022): n. pag.

[25] Alappatt, Valanto and Joe Prathap P. M.. "Trust-Based Energy Efficient Secure Multipath Routing in MANET Using LF-SSO and SH2E." International Journal of Computer Networks and Applications (2021): n. pag.

[26] DrishyaS., R. et al. "A Stable Clustering Scheme with Node Prediction in MANET." Int. J. Commun. Networks Inf. Secur. 13 (2021): n. pag.

[27] Ponguwala, Maitreyi and Sreenivasa Rao. "E2-SR: a novel energy-efficient secure routing scheme to protect MANET-IoT." IET Commun. 13 (2019): 3207-3216.

[28] Kondaiah, Ramireddy and BachalaSathyanarayana. "Trust Factor and Fuzzy Firefly Integrated Particle Swarm Optimization Based Intrusion Detection and Prevention System for Secure Routing of MANET." International Journal of Computer Networks & Communications 10 (2018): 13-33.

[29] Khan, Md. Sameeruddin and Md. Yusuf Mulge. "Efficient and Secure Data Transmission in MANETs against Malicious AttackUsing AODV Routing and PSO Clustering with AES Cryptography." (2017).

[30] Nagendranth, M. V. S. S. et al. "Type II fuzzy-based clustering with improved ant colony optimization-based routing (t2fcatr) protocol for secured data transmission in manet." The Journal of Supercomputing 78 (2022): 9102 - 9120.

[31] A.Karthik, Dr. J.L Mazher Iqbal. (2020). Performance estimation based recurrent-convolutional encoder decoder for speech enhancement. International Journal of Advanced Science and Technology, 29(05), 772 - 777. Retrieved from http://sersc.org/journals/index.php/IJAST/article/view/9611

[32] Sakkarapani, Krishnaveni and C. Chandra Prabha. "Secure Multi-Path Routing Using Splitting and Merging Based Clustering for Reducing Power Usage in MANET." (2021).

[33] Mohindra, AnubhutiRoda and Charu Gandhi. "A Secure Cryptography Based Clustering Mechanism for Improving the Data Transmission in MANET." (2021).

[34] Veeraiah, N. and B. Tirumala Krishna. "An approach for optimal-secure multi-path routing and intrusion detection in MANET." Evolutionary Intelligence 15 (2020): 1313-1327.

[35] Rani, Simpel. "A Hybrid and Secure Clustering Technique for Isolation of Black hole Attack in MANET." (2018).

[36] B, Revathi and Arulanandam K. "Design And Development of Robust And Secure Cluster Routing Algorithm For Manet Based IOT." International Journal of Computer Trends and Technology (2021): n. pag.

[37] Sajyth, RB and G. Sujatha. "Design of Data Confidential and Reliable Bee Clustering Routing Protocol in MANET." 2018 International Conference on Computer Communication and Informatics (ICCCI) (2018): 1-7.

[38] Rajaram, A., & Baskar, A. (2023).Hybrid Optimization-Based Multi-Path Routing for Dynamic Cluster-Based MANET. CYBERNETICS AND SYSTEMS.

[39] Karthik, A., MazherIqbal, J.L. Efficient Speech Enhancement Using Recurrent Convolution Encoder and Decoder. Wireless Pers Commun 119, 1959–1973 (2021). https://doi.org/10.1007/s11277-021-08313-6

[40] Anand, R. P., & Rajaram, A. (2020, December). Effective timer count scheduling with spectator routing using stifle restriction algorithm in manet. In IOP Conference series: materials science and engineering (Vol. 994, No. 1, p. 012031).IOP Publishing.

[41] Rathish, C. R., & Rajaram, A. (2018). Sweeping inclusive connectivity based routing in wireless sensor networks. ARPN Journal of Engineering and Applied Sciences, 3(5), 1752-1760.

[42] M. S. Gharajeh, "FSB-System: A Detection System for Fire, Suffocation, and Burn Based on Fuzzy Decision Making, MCDM, and RGB Model in Wireless Sensor Networks," Wireless Personal Communications, vol. 105, no. 4, pp. 1171–1213, Mar. 2019.

[43] M. S. Gharajeh, "A Neural-MCDM-Based Routing Protocol for Packet Transmission in Mobile Ad Hoc Networks," International Journal of Communication Networks and Distributed Systems, vol. 21, no. 4, pp. 496–527, Sept. 2018.

Cite this paper as:

Mazher Iqbal, J.L.; Senthil Kumar, M.; Mishra Geetishree ; Asha, G.R.; Saritha, Karthik, A; J.V.N.; BonthuKotaiah, N. (2023). Facial emotion recognition using geometrical features based deep learning techniques, *International Journal of Computers Communications* & *Control*, 18(4), 4644, 2023.
https://doi.org/10.15837/ijccc.2023.4.4644