

Hybrid Model for Human Emotion State Recognition using Deep Learning

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Abstract— Software application development for human emotion recognition is yet to optimize for utilization in medical applications to diagnose mental health. This proposed hybrid deep learning model evaluates the maximum score using CNN for facial emotion recognition and MFCC for voice emotion recognition. The maximum score function provides a unified result observed from two different recognition models. We use the FER dataset for facial and IEMOCAP dataset for speech emotion recognition. In this work, the real time video frames are extracted, segregated into image frames and audio blocks. The CNN model is used for facial expression recognition on video frames and MFCC is used for recognizing speech emotions. Both models execute independently and outcome convergence to produce combined results for recognizing human emotion state. The result shows that this new model performs better, and multiple test cases ensured the same by comparison to individual CNN for facial recognition and MFCC for speech emotion recognition.

Index Terms— Convolutional Neural Network, Emotion State Recognition, Speech, Facial Emotion.

I. INTRODUCTION

Application development using machine learning in this present decade is playing a marvelous role in human facial observations and emotion state recognition. Image processing for facial recognition using ML becomes an emerging field of computer enabled medical sciences which can be used for resolving the psychological problems in the medical field, forensic sciences, and health care sector. To enhance the performance of the emotion state recognition system, merging facial emotion recognition with speech recognition can be used. Emotions exposed by human trends to facial gestures and different speech slangs. These facial gestures are possible to detect using the application with ML model [6]. Certain facial expressions that humans express on their face and way they talk combinedly can help us to determine their emotion state accurately. These facial expressions can be stored in digital form in a three-dimensional matrix, and it is possible to retrieve the pattern in the facial expression. These patterns are datasets used to train the ML model for detecting the emotion state of a speaker. Similarly, extracted properties from the speech data is useful to train the ML model to extract the speaker's emotions. Facial expression accumulated with voice recognition can be used to optimize ML models to finalize the human emotion state. Facial expression recognitions and emotion classification achieved using Gabor filters [31], Histogram of Oriented Gradients [32], and Local Binary Pattern [12]. Similarly, for classification, logistic regression analysis, random

forest, support vector machine, and K-nearest Neighbour algorithm can also be used to classify the facial expression state [23]. CNN Applications reached almost in all fields in the computing sciences. The CNN model for intrusion detections [29] and electric network analysis [30] are notable applications in non-image processing. Alternatively, in image processing, CNN applications are widespread in almost all sectors such as space sciences, geographic information systems, transportation, security, and healthcare sectors. The CNN for human emotion state recognition can use in various fields like customer care, security, health care etc., Applications of human emotion recognition used to customer care services [24], health care [25], forensic, security, and intelligence bureau [26][27], etc., Deep learning for facial emotion recognition using CNN [28] and optimization using facial features using facial action coding system (FACS) achieved the considerable improvement in performance.

In parallel to facial image processing, speech processing applications are also concurrently increased to recognize the emotion state of a speaker. Different flavors of ML models are proposed for processing audio, sound, or speech data such that CNN [20], MFCC, LSTM [17], or SVM. MFCC is one among the finest method for processing sound to classify heart sound [14][15], smart home assistant [16], Multiscale deep convolutional long short-term memory (LSTM) framework for real time speech emotion recognition [17], and CNN for SER [18][19]. Fourier parameters contributed to recognizing speech emotions [21], and other speech models [22] also participated best in this field.

Facial and voice recognition are the most essential applications of image processing. Human face creates various expressions depending on their experiences. The objective is to improve feedback systems in hospitals and customer care services. Doctors are accepting to know how the patients are feeling about the treatment they are undergoing, whether they are feeling happy or not about the treatment. Continuing the patient's emotion state monitoring is a time, space and cost consuming process. This system can help the doctor with all these aspects. Whenever a patient feels discomfort at any situation, this human emotion state recognition system can be widely used in hospitals to improve the feedback system from the patients about their feeling towards the treatment they are undergoing to their doctor and help them to get immediate care and support during emergency situations and helps the doctors with monitoring their patients digitally from remote environment. This paper is organized into review of earlier research in this field. This method of human emotion state recognition is described in section 3, experimental outcomes are discussed in section 4, and conclusion at the end.

II. REVIEW OF LITERATURE

Health care and forensic sciences expect more optimal solutions from Information and computing technology to ease and resolve the problems which are not yet addressed. Psychological related treatment in the medical sector uses FER, which can help to measure a patient's emotion state with high precision. Machine intelligence for facial gesture extraction needs a large quantity of facial data set to train the model before going to implement. The data set for facial properties acquisition and evaluation is elaborately described [1] for Facial Emotion Recognition (FER). The survey covers the latest deep learning models available for FER and their corresponding pros and cons. The existing system for human emotion detection uses only facial expressions which is ultimately not sufficient to accurately predict human emotion state. To overcome this issue, naturally, human emotions are expressed not only on the face, but also through body language and speech.

Multiple features of an image can improve performance a deep learning. For emotion recognition, it is required to incorporate speech data along with facial data. This system is highly required for health care sciences to assess the emotional state of patients. To classify physically disabled and children with autism, facial points, and electroencephalograph (EEG) signals were identified from image to recognize emotional expressions. Here, detect facial points using CNN, long short-term memory has been used to classify and recognize facial emotion expressions [2]. It is ensured that real time emotion recognition is possible using this model. EEG signal processing is providing comfortable data for FER. The complete review of literature regarding emotion recognition using EEG has been analyzed and the role of deep learning and shallow machine learning is categorized. EEG data analysis and acquisition, EEG dataset management and data pre-processing are addressed to recognize FER [3] and human brain signals are trapped to recognize human emotion state [13].

CNN is an AI model for facial recognizing using deep learning. Here, background removal can improve better facial features and vector extraction. CNN is used for two different purposes, such that, remove background noise from the picture, and the second is for facial features vector extraction. The expression vector used to recognize five different types of facial expressions [4]. Facial recognition can be attained by a different style from CNN by adjusting the approach. Extracting local features from the face images using local gravitational force description and the retrieved descriptor is fed into a CNN. The DCNN has two branches which explore geometric features such as edges, curves, and lines whereas holistic features are extracted by the second branch. The score will merge

to the final classification score [5]. A system using a single recognition system cannot give accurate results for all situations. These systems use live face recognition to detect emotions from time to time on a lively basis. The emotions during live recognition might fluctuate without giving a steady emotion throughout.

Emotion-aware mobile applications are increased due to its smart features, performance, attractions, and user usability. To use those applications, an emotion recognition system should be in real time and high-precision. In our model, video frames are segregated and a face detection module is applied to extract the face regions in the frames. The dominant region is then fed into a Gaussian mixture model-based classifier for emotion classification [7]. Similarly, image processing for facial emotion recognition appended in the Humanoids. Robots are developed to identify the emotional state of a person to improve human–robot interaction (HRI)[8]. The robot with camera eyes can observe the user's facial and recognize users' emotions, and respond appropriately.

Spectral subtraction and linear predictive coding with MFCC voice denoising is achieved to recognize speech emotion recognition. The CNN model used for speech emotion recognition [9]. Alternatively, A hybrid model [10] has been proposed to enhance the SER performance, which comprises advantages of different models to attain better performance. Deep neural network (DNN), CNN, and recurrent neural network (RNN) have been taken to find out the best combination for SER. Integration of distinct methods for SER can be used to aggregate the different features for improving the performance compared to the individual SER methods with different parameters. DNN, CNN, and RNN has been aggregated to recognize four emotions such as angry, happy, neutral, and sad [10]. RNN classifier with Mel frequency cepstrum coefficients (MFCC), and modulation spectral features (MSFs) on Berlin and Spanish data set performs better compared to Multivariate Linear Regression (MLR) and SVM [11]. A common framework proposed to use interdependent features of DNN, CNN, and RNN to obtain generalized features for SER, and have achieved 57.1 % on weighted accuracy and 58.3% on unweighted accuracy over IEMOCAP dataset. SER can be achieved through various existing algorithms along with different parameters and features.

III. HUMAN EMOTION STATE RECOGNITION

During the digital era, machine intelligence is ubiquitous in almost all fields. Deep learning in artificial intelligence (AI) reached the next stage in advancement of emotion state recognition of a speaker in real-time basis. Two ways the emotion states can be the machine, such that, either speech or facial emotion recognition. To improve the performance human emotion state recognition using AI system, it is mandatory to convergence of both facial and speech recognition together to get high precision outcomes. The prominent work of this model is to fusion the outcomes of CNN for facial expression and MFCC for speech emotion recognition in certain ratios to finalize the emotion state. The independent features of CNN and MFCC have been utilized without altering its functional properties for quantitative and qualitative feature extraction from the dataset.

A. General Consideration

1. Offline videos used to test the system.
2. Only the English language is considered testing.
3. Facial and Speech expressions are independently handled.

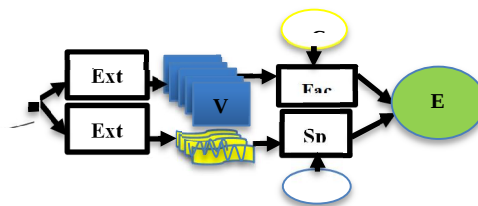


Fig. 1. Architecture Diagram

B. CNN for Facial Expression Recognition

The outperformance features of CNN help the machine to learn and classify the images. The CNN consists of multiple convolutional layers followed by pooling layers to extract facial properties in local patterns, and fully connected layers for global pattern recognition. The output layer with neurons produces the features corresponding to the emotions to be recognized.

Preliminary process is to convert the video frame into gray-scale images, extracting important pixels from the image and summarize using filters/kernels. For faster execution, the max-pooling layer is used to reduce the

dimensionality of the input vector. The max-pooling filter passed through the data and highest value is extracted as the final feature. The final step in CNN model is flattening which is extracting various emotion features from the image and classify it. Here, the input is defined in ' f ' and the trained pattern is ' h .' The results matrix marked as $G[m,n]$ shown in equation 1 below.

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k j[j,k] f[m-j, n-k] \quad \text{--- (1)}$$

The output matrix dimension considering of padding and stride, and is calculated using given equation

$$n_{out} = \left\lceil \frac{n_{in} + 2p - f}{s} + 1 \right\rceil \quad \text{--- (2)}$$

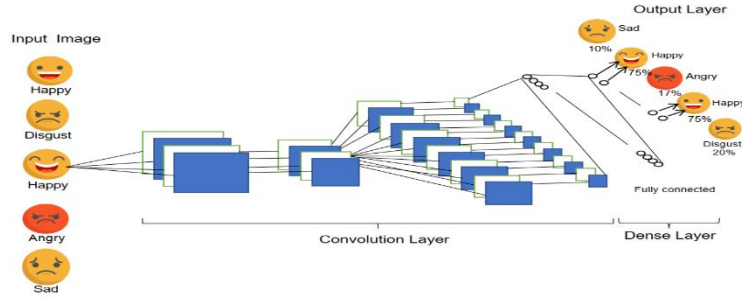


Fig. 2. Facial emotion Classification Using CNN

The resultant matrix calculated using the equation 3, given below. It classifies the different facial emotions and compares them with the labeled facial emotions stored in the matrix to finalize the emotion state.

$$dA = \sum_{m=0}^{n_h} \sum_{n=0}^{n_w} W \cdot dZ[m,n] \quad \text{--- (3)}$$

The CNN model was developed to classify the emotional state of the speaker. The output matrix ensures that the proposed CNN model completes the design objectives by classifying the emotion state of the speaker.

C. MFCC for Speech Emotion Recognition

Speech data is converted to digital form at 44.1 kHz using the sampling process shown in figure 1. To extract various emotion patterns, the voice data is divided into frames. Each frame is windowed using a Hamming window.

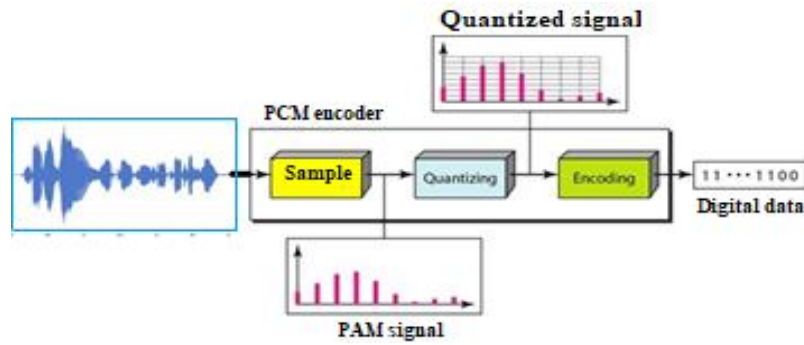


Fig. 3. Analog data encoding

Later, all frames are converted to frequency domain using a short time Fourier Transform. Meanwhile, a certain number of sub-band energies are calculated using a Mel filter bank, which is a nonlinear- scale filter bank that imitates a human's aural system and sub-band energies are calculated. Finally, the MFCC is computed by an inverse Fourier Transform. The process of MFCC shown in figure 4.

$$mel(f) = 1127 \ln \left(1 + \frac{f}{700} \right) \quad \text{--- (4)}$$

$$energy = \sum_{t=t_1}^{t_2} x^2[t] \quad \text{--- (5)}$$

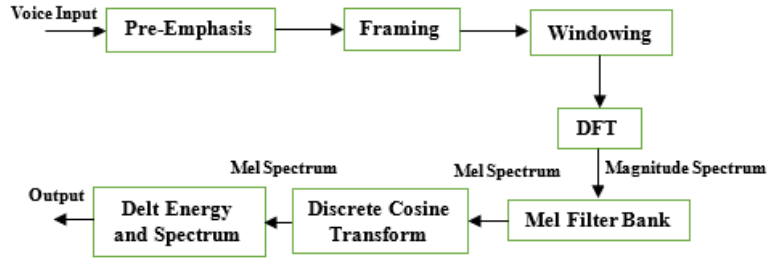


Fig. 4. MFCC Conversion

First the voice data is divided into frame. Each frame is windowed using Hamming window

$$W(n) = 0.54 - 0.46 \cos \frac{2\pi * n}{N - 1} \quad - - - (6)$$

Where $W(n)$ – value of the window at sample index ‘ n ’, N – length of window, and π – is a constant, its value equal to 3.14. In continue to this, the data frames are converted to frequency domain using a Short Time Fourier Transform (STFT), The mathematical formula for the STFT is as follows:

$$STFT(t, \omega) = \int \{ -\alpha \}^{|t|} x(\tau - t) e^{-j\omega\tau} d\tau \quad - - - (7)$$

Where, ‘ t ’ is the time index of the window, ‘ ω ’ is the frequency index, and ‘ $x(\tau)$ ’ is the original signal ‘ $w(\tau - t)$ ’ is a window function centered at time ‘ t ’, ‘ j ’, is the imaginary unit. Significant number of ‘*sub-band*’ energies are calculated using a ‘*Mel filter bank*’, which is a nonlinear- scale filter bank that imitates a human’s aural system.

$$Mel(f) = 2595 * \log_{10} \left(1 + \frac{f}{700} \right) \quad - - - (8)$$

Where ‘ f ’ is the frequency in Hz.

D. Convergence of cnn and mfcc

The prominent work of this research is to improve the performance of the human emotion recognition system, which is integrating facial expression and voice data to get a unified, enhanced emotion state recognition system. The unique features of CNN and MFCC pairs are summed, and the highest value for the corresponding emotion state is finalized.

TABLE 1. WEIGHT BASED EMOTION STATE RECOGNITION

Emotion State	Facial Expression CNN	Value	Emotion State	Voice Expression MFCC	Value	Augmented Maximum Weight	Human Emotion State
1	Happy	62%	1	Happy	14%	76%	Neutral
2	Sad	34%	2	Sad	12%	46%	
3	Angry	28%	3	Angry	10%	38%	
4	Neutral	54%	4	Neutral	23%	77%	

Table 1 shows the human emotion state for final emotion weight calculation. To finalize the ultimate emotion state of a speaker, two sets labelled emotions states for speech and facial expressions are kept in two different arrays.

Facial Emotion State (FES) = [‘ Happy’ , ‘ Sad’ , ‘ Angry’ , ‘Neutral’ ,]

Speech Emotion State (SES) = [‘ Happy’ , ‘ Sad’ , ‘ Angry’ , ‘Neutral’ ,]

$$FES[i] = \max(CNN(IS))$$

$$SES[i] = \max(MFCC(VS))$$

$$HESR = \max \{ (FES1 + SES1), (FES2 + SES2), \dots, (FESn + SESn) \} \quad - - - (9)$$

$$HESR = \max \left(\sum_{i=1}^n (FESi + SESi) \right) \quad - - - (10)$$

The highest augmented score or weight of the FES and SES considered for selecting the appropriate emotion state label to finalize.

$$HESR = \max(CNN(Image_i) + MFCC(Audio_i)) \quad - - - (11)$$

This research and experiments gives the highest importance of facial expression because human emotions will immediately reflect on the face, and which is difficult to control however voice emotion control.

IV. RESULTS AND DISCUSSIONS

Convergence of facial emotions and speech emotions using CNN and MFCC is implemented using Python. Here, OpenCV is a computer vision object that is implemented as library files, and 'TensorFlow' used for object detection. Here, multi-scale low ranking matrix model have been utilized for reducing the size of the input image matrix to improve performance. We segregated the video frames and speech data separately. Later, facial feature extraction and classification, removal of irrelevant visual components aided by facial detection are accomplished, which is a key step in emotion identification. The facial components are used to extract emotion detection characteristics. Sample code for facial emotion detection is given in figure 5. Speech emotion recognition achieved using MFCC by implementing 'librosa', 'sklearn', and 'Kerosene'. All the library files along with the MFCC function are used to classify the emotions state of a speaker. The convergence of the results from both the models detected the emotion state of a person. To experiment with the proposed model, OpenCV has been used. The OpenCV provides a set of predefined library files for classification. The 'keras', 'librosa', and 'tensorflow' have been used here to recognize voice emotion.

```
face_classifier=cv2.CascadeClassifier("path")
Classifier = load_model(model)
Emotion_labels=['Angry', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad', 'Surprise']
Cap=cv2.VideoCapture(0)
Prediction= classifier.predict(x)[0]
```

Fig. 5. Video Frames Extraction

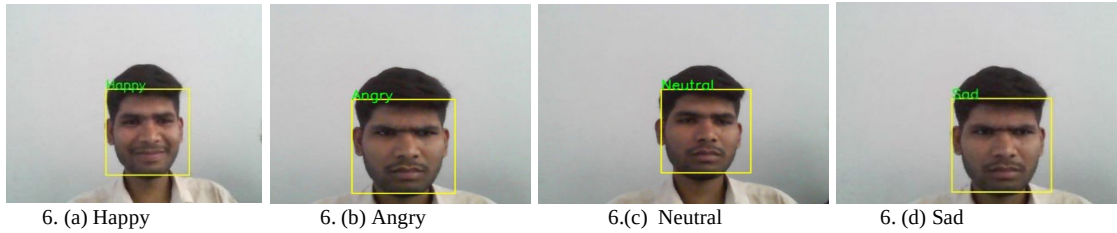


Fig. 6. Facial Emotion Recognition

Figure 6 shows the various facial emotion states while testing our proposed system.

```
mfcc=pd.Series(demo_mfcc)
pit = pd.Series(demo_pitch)
mag=pd.Series(demo_mag)
c=pd.Series(demo_chrom)
```

Fig. 7. Sample Code for Speech Emotion State Extraction

For speech emotion recognition, we build the model using 'librosa' and 'sklearn' and 'RAVDESS' data used to train and test for different speech modulation irrespective of male, female, or children.



Fig. 8.a. Happy Emotion State



Fig. 8.b Neutral Emotion State

Fig. 8. Speech Emotion State Extraction

The score for the emotion state using CNN FES = [60, 35, 40, 50] and the MFCC is SES= [10, 20, 10, 25]. The addition of two outcomes from CNN and MFCC combined results shows that CNN conveys 'Happy' but the MFCC conveys 'Neutral.' To integrate the result, the maximum probability is classified into 'Neutral.' Figure 9 shows the difference between the training data set and the validation.

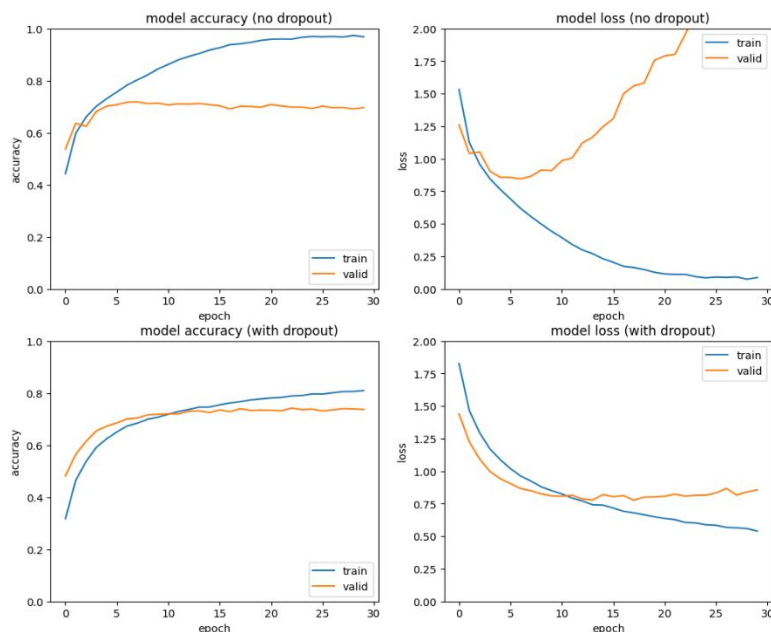


Fig. 9 Epoch history of CNN+MFCC for human emotion state recognition

Performance of the computing machine is yet to optimize for neutralizing human performance in various aspects. Deep learning can address unsolved problems in health and elderly care sector. In this research work, the performance of deep learning for human emotion state recognition is enhanced by merging of CNN for facial expression recognition and MFCC for voice recognition. Here, the fusion of CNN and MFCC have provided high precision results with the combination of 75:25 ratio. The facial data stored on the vector and the voice data stored in the linear array. The outperformance of the proposed work ensures that this model performs better to recognize the emotion state of a person compared to other existing models.

V. CONCLUSIONS

Performance of the computing machine is yet to optimize for neutralizing human performance in various aspects. Deep learning can address unsolved problems in health and elderly care sector. In this research work, the performance of deep learning for human emotion state recognition is enhanced by merging of CNN for facial expression recognition and MFCC for voice recognition. Here, the fusion of CNN and MFCC have provided high precision results with the combination of 75:25 ratio. The facial data stored on the vector and the voice data stored in the linear array. The outperformance of the proposed work ensures that this model performs better to recognize the emotion state of a person compared to other existing models.

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