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Cartoon Movie Recommendation Process through Convolution Neural network

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Abstract

There have been massive developments in the cartoon industry which has been growing considerably with a large section of the entertainment industry that are interconnected with the other industries such as Digital Media, Gaming, etc. The cartoon animation is massive and has large scale ramifications on the adolescent populations as most of these animations are catered to this section ofthe population. That does not mean that it is exclusively targeted towards the younger population as there are animations that are made for an adult audience too, which contain a lot of graphic imagery and other negative emotions. The cartoon animations with a large concentration of negative emotions are not suited for the kids as it can leave a lasting impact on their psyche. There is a need for an automatic cartoon movie analysis andrecommendation mechanism based on the percentage of the emotions depicted in the movie. If there are more negative emotions then the movie is considered as negative and if there are more positive emotions shown in the movie it will be considered as a positive movie and recommended to the user. Therefore, this research article facilitates the development of a cartoon emotion recognition approach that trains the Convolutional Neural Network on a cartoon emotion database the outcomes from which are effectively classified using Fuzzy classification. The evaluation of the accuracy of the emotion recognition has been put under the hammer to achieve extremely promising results.

Keywords— *Emotion Recognition, Convolutional Neural Network, Decision Making, Fuzzy Classification.*

I. INTRODUCTION

Mainstream social psychologists argue that emotion, along with basic mental functions such as observation, understanding, memorizing, and articulating, is a significant cognitive function. Unlike computers, individuals have innately complicated emotional processes, and emotions have a major effect on behavior. To properly grasp emotional responses, computers must create a more sophisticated and realistic human communication infrastructure.

Emotion is an important aspect of human conversations because it impacts relationship cohesiveness and consequence. Automated emotion detection in cartoon characters can aid human-centered and expressive measures by enabling collected emotional information is being utilized to assess, convey, and understand the animation's characteristics [1]. Furthermore, owing to the complexity and unpredictable aspects of emotional expressions, specifically in regard to the conflicting strategic elements that appear when a character interacts, implementing such strategies is difficult. With the fast advancement of technology and human interface features, there is an undeniable demand for more complicated and sympathetic physiological interaction in the realm of cartoon expression assessment.

Psychological contextual knowledge, pertaining to several disciplines of research, may have a significant influence on the perceived sense emotions in expressions. Human expressions are common environmental signals in personal communication and convey important informationparticularly when we are accompanied by someone else. Emotion recognition has emerged as a feasible research area with a wide range of implications. It may also be used in animation, for instance, to get an emotional comprehension of the events in order to convey human behavioral patterns.

Racial identity influences ordinary physiological interactions in social contexts, as well as other people's reactions frequently provide more information. This relationship between cultures is especially useful in ambiguous scenarios when essential information may be obtained from those other people's emotional stimuli in orderto adequately analyze the situation. The difficulty of employing computer-generated gestural signs to study such complicated social relationships may be overcome.

The establishment of such a system enables for the supervision of animated content, which differs from traditionalemotion detection. Moreover, the characters' interaction, while based after human nature, is creative and takes a variety of freedoms that can be complicated to understand automatically using image processing techniques [2]. To address this issue, the current study draws on previous research that studied how different face areas are employed during visual cues and if that knowledge may be used to establish and develop an original cartoon emotion identification system. Disposition, linguistic tone, and linguistic competence are all factors that influence physical expressiveness when communicating. This will aid inthe effective execution of the cartoon's abstract framework by better regulating the content.

The concept that comparable facial motions can be transformed by different viewpoints, which could be difficult to determine, is a basic difficulty in automated emotional identification. Likewise, astonishment-inducing eyebrowmovements have features with intensity-inducing expressions. Having studied classic emotion recognition techniques in order to construct our strategy for cartoon emotion detection, and we opted to employ Convolutional Neural Networks for this objective due to its effective reliability and especially powerful deployments in computer vision. The technique has been thoroughly analyzed and assessed through the utilization of experiments, which are explained in the subsequentportions of this research paper.

The second half of this research article is a literature review. The proposed approach is described in section 3, and the acquired findings are carefully assessed in part 4. This study article is finalized in the section 5 including the extent ofthe future improvements.

II. LITERATURE SURVEY

According to Chenghao Zhang [3], there has been a surge in the number of solutions that will profit from determining or identifying emotional responses. Suchemotions have been critical in many deployments that can grasp a human being's mental state. Emotion identification canbe effective in giving vital feedback to enhance the human communication technique. The authors of this paper suggest using an effective framework that incorporates emotion integration and an autoencoder to perform emotion recognition in voice signals. The conclusions have been evaluated and found to be quite favorable.

Jing Han [4] reveals and there has been an enhanced involvement among these academic institutions for the goal of accomplishing appropriate and fully automated emotion recognition via the examination of human facial characteristics. Significant developments in the technology have been made in recent years, with the goal of enhancing the performance and quality of emotion identification in order to provide precise and rapid outcomes. The bulk of methodologies have been used to perform emotion recognition using input photos containing face characteristics. Thistechnique presents an efficient strategy for utilizing cross-modal emotion anchoring for the goal of learning and enhancing the emotion detection strategy in a monomialstructure.

T. Zhang [5] provides a practical and usable framework for establishing functional emotion classification that may be used in a variety of different settings. The researchers of this study suggested an efficient method for emotion recognition that makes use of Recurrent Neural Networks. The researchersimproved the reliability of the recognition by modifying the recurrent neural networks with spatio-temporal properties. The authors have used the spatiotemporal and hidden aspects that are represented irregularly to boost the methodology's capacity to distinguish. The strategy has been properly examined in order to produce operational outcomes which have been demonstrated to outperform over traditional means.

Hongli Zhang [6] proposes BDAE constituent unificationas a multi-modal mood detection technique combining expressive information and EEG data, using emotion data and EEG statistics as emotional processing. As per experimentresults using the provided video footage to execute supervised learning training operations on the recommended approach, the formation of Eeg data and expression features may significantly boost the capacity to discriminate emotional responses. Deep neural networks could also significantly improve the ability to identify multi-modal emotions. When compared to previous approaches, the proposed strategy produces considerable increases in detection accuracy.

Haimin Zhang [7] proposed a learning-based end-to-end architecture for visible emotion recognition relying on poorly controlled emotion strengths. The proposed framework comprises of being a first classification flow, an emotion intensity prediction stream, and a second classification flow. The intensity representation pathway, which would be built onthe FPN's culmination, predicts emotional intensity translations connected with the source images. The expected intensity mapping is incorporated into the subsequent classification flow for eventual recognition of facial expression. The authors proved empirically the proposed system for both image emotion detection and emotional analysis using a multitude of baseline methodologies. In terms of dependability, the experimental results reveal that the proposed network beats existing approaches.

The Conversational Transformer Network, according to Zheng Lian [8], is a cross, inter framework for identifying conversational emotion. The Conversational Transformer Network simulates inter-modality and intra-modality interactions for multimodal features. Conversely, throughout the discourse, the Multimodal Transformer Interconnection brings viewpoint and speech linkages into consideration. The utility of the Conversational Transformer Network is provedby the outcomes of two significant benchmarking challenges.

The proposed approach sets a new standard for identifying conversational emotions. Investigations on various paradigms also show the significance of multimodal confluence.

[9] C. Mumenthaler Investigate the influence of higher socioeconomic logical deduction structures on the categorization of social emotions. Scholars were able to explore this complex system because of artificial facial reactions, which allowed them to replicate a discussion between many characters while keeping absolute control over the inputs. Finally, this study highlights the importance ofsocial background information in reading facial expressions. Although the findings may be extended to all contradictory facial expressions, they do highlight that future iterations of emotion recognition must consider the influence of contextual variables, notably the socio-affective interpretative mechanisms that play a significant role.

Najmeh Samadiani [10] implies that distinct investigations have already been undertaken for the intention of emotion classification, and this methodology offers a significant direction for acknowledging positive emotion from unsupervised movies to use a composite neural network. Because ResNet structures perform well in emotion classification, the researchers used the Inception-ResNet architecture to extract the spatio-temporal properties in the proposed technique. An LSTM layer was used to the recovered attributes to analyze the temporal dynamic features in the subsequent frames. Considering geometric properties formed by feature points are effective at identifying emotions, the researcher utilized CNN to determine deep features offacial separation time series. By combining existing those essential traits at both the element and judgment level combinations, these techniques classified joyful and unhappy subgroups.

Jinpeng Li [11] describes that the sentimentality of the fellow humans plays a significant role in the communication between the two distinct individuals around the world. Emotions are important in comprehending and realizing the components of nonverbal signals. The absence of emotion classification in computer-human communication leads to poor understanding. This lack of perspective leads to confusion, which may be difficult to manage. As a result, thereis a requirement for an effective and convenient method for creating an enhancement in communication employing an electroencephalogram approach for identifying emotionalresponses.

Tengfei Song [12] narrates that a granular emotion categorization MPED was shown. The MPED is composed of several humans' multi-modal physiological parameters. Each participant viewed video clips depicting seven different emotional responses: indifference, anxiety, contempt, grief,wrath, humor, and enjoyment. The material of such short videos was evaluated using psychological tests. Participants assessing information extraction elements have a similar ethnic background to those participating in the emotional inference research, thus overall understanding will be equivalent. To prevent exhausting participants by minimizing their time attempting the experimental devices, the self- assessment across sensor data acquisition was put towards to the conclusion of the studies that provided good results.

Yelin Kim [13] describes a technique for identifying emotions in user dialogue. In this method, the two major sources of facial modulations generated by speech areaddressing stress and the spoken pronunciation. ISLA's categorization and labeling steps are based on the features of these variances. The article looks at how the ISLA application's findings might be combined with speech-based emotional evaluations. The researchers evaluate the proportionate role of the bottom jaw, top chin, and speech aspects in emotional recognition and develop an auditory categorization method that effectively analyzing information about the content from these subcategories.

Chunmei Qing [14] states that there is a lack of an effective emotion categorization technique for analyzing and understanding human sentiments, according the researcher. The recognition of genuine emotion would've been useful in a range of situations when the accumulated and identified emotions would be advantageous. The authors of this work suggest using EEG data to construct a coefficients-based approach based on computer intelligence. This approach outperformed the baseline procedures and not only in order to ensure consistency, but also in terms of practicality. To commence, the authors employed machine learning techniques to extract features from EEG data and identify emotions. The researchers also revealed that the last phases of EEG waves contain more emotional links, leading to an improved classifier as determined by extensive study.

III PROPOSED METHODOLOGY

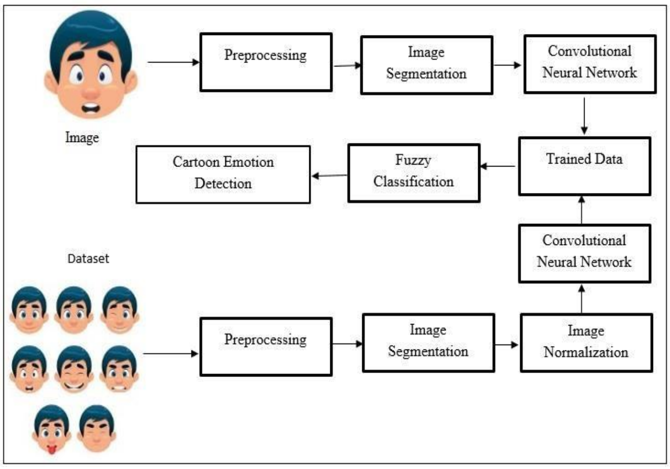

Figure 1: System Overview Diagram

The proposed approach for detecting cartoon emotions is displayed in picture 1 above. The following stages are used in the provided strategy to attain the specified goals for cartoon emotion detection.

Step 1: Dataset Formation – The presented approach is initiated by achieving the emotion input of cartoon characters for the purpose of identification. The cartoon character chhota bheem is selected for this purpose and the videos of the same are provided to the frame extraction module. These videos are downloaded from the YouTube streaming platform. The frame extraction module is being utilized for the purpose of extracting the frames of the input video through the use of OpenCV library. The path of the video directory is provided to the module which extracts the individual frames from the video into a predetermined path.

The extracted frames are segregated into different folder each of which pertaining to a specific emotion. The 5 fundamental emotions are being considered for our implementation, namely, angry, disappointed, disgusted, happy and sad. These folders are populated accordingly which results in the creation of the dataset for input. The dataset is then effectively divided into training and testing images. The 1302 images are selected as training images and are provided to the training module for the purpose of training the Convolutional Neural Network.

Step 2: Preprocessing and Image Segmentation – The dataset images extracted from the input video of the cartoon character in the previous step need to be preprocessed before being provided to the Convolutional Neural Network for training purposes. The preprocessing module is provided the path containing the dataset images which are read using the OpenCv library. These images are initially converted into grayscale color model and then resized into a dimension of 170x170. This procedure is repeated for all the images in the dataset to achieve the preprocessed images in a dedicated directory.

Step 3: Image Normalization – The preprocessed images are provided as an input to this module which sets the training and testing dataset paths. Once these two paths have been set, this module assigns a batch size of 32 which represents the maximum number of images that are utilized by the model for a particular instance. As the batch size is set the model allocates 100 epochs which is the frequency of deployment of the neural network to perform the training on the images being provided as an input. well as respective 170 X 170 size factor. Following this, the object is given a batch size, as well as a color mode of gray scale and a class mode of categorical. The class mode is configured to categorical to differentiate the learning process into five categories of emotions: angry, disappointed, disgusted, happy and sad.

Step 4: Training with Convolutional Neural Network – A sequential class is employed to specify the sort of neural network object to be referred to as a model. Since grayscale images are used, the first layer of the convolution neural network has 32 kernels of size 3x3 having activation function 'Relu' and input resolution of 170x170 with color channelvalue as 1. A subsequent layer of convolution neural network containing 64 kernels of size 3x3 and activation function 'ReLU' is established, accompanied by a max pooling layer with kernel size 2x2 to differentiate the trained neuron havinga drop rate of 25%.

Towards the third layer of a convolution neural network, 128 kernels of size 3 X3 being activated with the activation function 'ReLU,' supplemented by a max pooling layer of size 2 X2. The identical procedure is conducted to the fourth layer, resulting in a 25% dropout rate.

The neural network object was flattened after four layers through using the method flattens. The learned neurons are then gathered using a dense layer with a bucket size of 1024 and an activation function of 'ReLU'. To maintain the optimum trained neurons, a 50% dropout rate is given to these aggregated neurons. Employing additional dense layer and a 'softmax' activation function, the neurons are sorted into five classes.

Following the completion of the preceding processes, theneural network model is constructed through the use of an Adam Optimizer with an accuracy of 0.0001 as well as adecay value of 10-6. The neural network object was thus enabled to begin training through using fit generation function for the specified batch size, frequency of epochs, also withtest, train data generator objects to get trained data in a specific file format called .h5. Figure 2 depicts the entire training procedure using the architecture of a Convolutionneural network. The equations 1 and 2 below display the ReLU and Softmax functions respectively.

$f(x) = max(0, x)$ ____________ (1)

The module then employs a rescaling factor of 1:255 after the creation of the ImageDataGenerator object as an investigation ratio of the training images. By selecting this factor, 1/255th of a pixel value is also configured to be evaluated during training the images for cartoon emotion recognition. This ImageDataGenerator object is being employed to establish the train and test directory locations, as

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Where

x/e is the input to a neuron______(2)

Layer	Activation
CONV 2D 32 X 3 X 3	Relu
CONV 2D 64 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
Flatten	
Dense 1024	Relu
Dropout 0.25	
Dense 2	Softmax
Adam Optimizer	

Figure 2: CNN Architecture

Step 5: Testing and Fuzzy Classification – This stage of the process entails bringing the system through its testing phase in terms of cartoon emotion detection. This stage of the procedure uses the test cartoon video as input. When the testing video is submitted, it is treated to the initially stated frame extraction and preprocessing. The preprocessed image is then normalized by the image normalization component. The image is then presented to the deep learning model, which consists of an a.h5 file, in order to achieve the maximum corresponding emotions.

The Convolutional Neural Network is continually processing and integrating the ideal corresponding emotions caused by the trained h5 file to a list. The list summarizes the different emotions that have been identified.

The maximum number of best-matched emotions derived from the recorded images is retrieved, while the lowest number is assigned to 1. The difference between both maximum and minimum count is determined and

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separated into five classes, which are referenced to as fuzzy crisp values: VERY LOW, LOW, MEDIUM, HIGH, and VERY HIGH.

The cartoon emotions are furthermore evaluated for their presence in the VERY HIGH classes based on a predefined threshold. When a sentiment in a cartoon figure is identified, itis displayed as an output to the user.

IV RESULT AND DISCUSSIONS

The proposed strategy for cartoon emotion detection was realized utilizing the Python programming language and the establishment of Convolutional Neural Networks. The technique was created with the help of the Spyder IDE. The laptop used for the implementation has an Intel Core i5 CPU, 8GB of primary storage, and a 1 TB hard disk.

The operator feeds the relevant cartoon character facial footage into this process to detect the character's sentiment. The fundamental framework that can only be evaluated in attempt to appropriately recognize the emotion is the Convolutional Neural Network. The operational evaluation is required to identify any discrepancies in the model's execution. The assessment process is described underneath.

Performance Evaluation through Root Mean SquareApproach

Several tests were conducted to establish the error produced by the suggested approach, the process for cartoon emotion recognition employing Convolutional neural networks. The decreased accuracy reached by the approaches attributable to the cartoon emotion detection approach's predisposition for error may be utilized to define the predefined threshold.

The Root Mean Square Error, or RMSE, is used to calculate the error caused by the specified approach. The presence of any type of inaccuracy in the suggested strategy for cartoon emotion recognition through CNN indicates the operational feasibility of the proposed methodology. The RMSE approach makes it easier to calculate errors between two continuously connected parameters. The metrics tested in this technique are the anticipated cartoon emotion identification and the achieved cartoon emotion identification. Equation 1 is used to compute the error estimates.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{1,i} - x_{2,i}\right)^2}{n}} \quad \_ (3)$$

Where,

$\sum$ - Summation

$(x_1 - x_2)^2$ - Differences Squared for the summation in between the expected No. of cartoon emotion identifications and the obtained No of cartoon emotion identifications

n - Number of Trails

These two properties were measured on 5 distinct video inputs on each of the emotions being tested, namely, angry, sad, disgusted, disappointed and happy. The outcomes of theseassessments are depicted in table 1 below.

Cartoon Emotion	No. of expected Cartoon Emotion Identifications	No. of obtained Cartoon Emotion Identifications	MSE
Angry	5	5	0
Happy	5	5	0
Sad	5	5	0
Disgusted	5	5	0
Disappointed	5	4	1

Table 1: Mean Square Error measurement

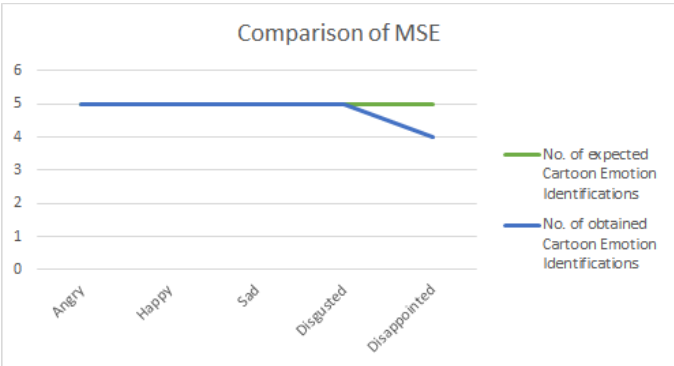

Figure 3: Comparison of MSE in between Expected No ofcartoon emotion recognition V/s obtained No of cartoon
emotion recognition

The experimental analysis of the concept's outputs have made it simpler to comprehend the error rate visually, as illustrated in figure 3. The graph shows the system's error rate in guessing the emotion of animated characters relying ontheir face expressions.

The RMSE scores analyzed for cartoon emotion detection confirmed the efficacy of the proposed approach in considerable detail. The suggested method outperformed the Facial Emotion Recognition methodology published in [15]. Our method achieves an RMSE of Table 2 below shows a tabular comparison of the Facial Emotion Recognition approach with the offered methodology.

Performance Metric	Our approach (CNN)	Facial Emotion Recognition approach [15]
RMSE	0.44721	0.6381

Table 2: Comparison with [15]

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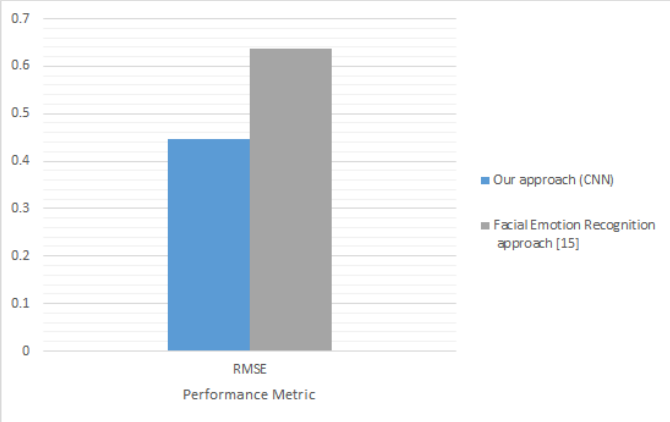

Figure 4: Comparison with Facial Emotion recognition technique in [15]

The deep learning algorithm suggested in this research work dependably surpasses the Facial Emotion Recognition technique described in [15], as seen in Figure 4. This is owing to the Convolutional Neural Network's extremely accurate implementation, which dramatically enhances detection capability. The Fuzzy classification technique maximizes the outcomes, as seen by MSE and RMSE values of 0.6 and 0.44721, respectively. This evaluation reveals the exact and accurate application of the cartoon emotion detection technology for the suggestion of animated movies.

V CONCLUSION AND FUTURE SCOPE

The research framework for the objective of cartoon emotion identification using the character's face expression for movie recommendation has been realized through use of Convolutional Neural Networks and Fuzzy Classification. The frames displaying the character's facial expression are provided as an input to the proposed approach. After appropriate preprocessing, these images are efficiently retrieved and used for normalization through the image normalization approach. The Features are utilized to identify regions from the preprocessed and normalized frames. The CNN method utilizes these images as an input to do facial expression recognition. The CNN approach is previously trained on the cartoon facial images which too are preprocessed and normalized. The CNN is trained for 100epochs on such images to achieve model file which is then used for the detection of the cartoon emotion recognition. Thisis performed iteratively for the input frames. The output of this execution and detection is classified using the Fuzzy classification to obtain accurate cartoon emotion detection,which will then be utilized to recommend the movie. Themood detection approach's performance was proven by the experimental assessment.

For the purpose of future research directions, the approach can be converted into an API for easier integration. This can be also improved to allow for grading animated or cartoonmovies automatically.

REFERENCES

[1] S. Lee, D. K. Han and H. Ko, "Multimodal Emotion Recognition Fusion Analysis Adapting BERT With Heterogeneous Feature Unification," in IEEE Access, vol. 9, pp. 94557-94572, 2021, doi: 10.1109/ACCESS.2021.3092735.

[2] Q. Mao, Q. Zhu, Q. Rao, H. Jia and S. Luo, "Learning Hierarchical Emotion Context for Continuous Dimensional Emotion Recognition From Video Sequences," in IEEE Access, vol. 7, pp. 62894-62903, 2019, doi:10.1109/ACCESS.2019.2916211.

[3] C. Zhang and L. Xue, "Autoencoder With Emotion Embedding for Speech Emotion Recognition," in IEEEAccess, vol. 9, pp. 51231-51241, 2021, doi:10.1109/ACCESS.2021.3069818.

[4] J. Han, Z. Zhang, Z. Ren and B. Schuller, "EmoBed:Strengthening Monomodal Emotion Recognition via Training with Cross-modal Emotion Embeddings," in IEEE Transactions on Affective Computing, vol. 12, no. 3, pp. 553- 564, 1 July-Sept. 2021, doi: 10.1109/TAFFC.2019.2928297.

[5] T. Zhang, W. Zheng, Z. Cui, Y. Zong and Y. Li, "Spatial– Temporal Recurrent Neural Network for Emotion Recognition," in IEEE Transactions on Cybernetics, vol. 49, no. 3, pp. 839-847, March 2019, doi: 10.1109/TCYB.2017.2788081.

[6] H. Zhang, "Expression-EEG Based Collaborative Multimodal Emotion Recognition Using Deep Auto-Encoder,"in IEEE Access, vol. 8, pp. 164130-164143, 2020, doi: 10.1109/ACCESS.2020.3021994.

[7] H. Zhang and M. Xu, "Weakly Supervised Emotion Intensity Prediction for Recognition of Emotions in Images,"in IEEE Transactions on Multimedia, vol. 23, pp. 2033-2044, 2021, doi: 10.1109/TMM.2020.3007352.

[8] Z. Lian, B. Liu and J. Tao, "CTNet: Conversational Transformer Network for Emotion Recognition," in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 29, pp. 985-1000, 2021, doi: 10.1109/TASLP.2021.3049898.

[9] C. Mumenthaler, D. Sander and A. S. R. Manstead, "Emotion Recognition in Simulated Social Interactions," in IEEE Transactions on Affective Computing, vol. 11, no. 2, pp.308-312, 1 April-June 2020, doi: 10.1109/TAFFC.2018.2799593. N. Samadiani, G. Huang, Y. Hu and X. Li, "Happy Emotion Recognition From Unconstrained Videos Using 3D Hybrid Deep Features," in IEEE Access, vol. 9, pp. 35524- 35538, 2021, doi: 10.1109/ACCESS.2021.3061744.

[10] J. Li, S. Qiu, Y. -Y. Shen, C. -L. Liu and H. He, "Multisource Transfer Learning for Cross-Subject EEG Emotion Recognition," in IEEE Transactions on Cybernetics, vol. 50, no. 7, pp. 3281-3293, July 2020, doi: 10.1109/TCYB.2019.2904052.

[11] T. Song, W. Zheng, C. Lu, Y. Zong, X. Zhang and Z. Cui, "MPED: A Multi-Modal Physiological Emotion Database for Discrete Emotion Recognition," in IEEE Access, vol. 7, pp. 12177-12191, 2019, doi: 10.1109/ACCESS.2019.2891579.

[12] Y. Kim and E. M. Provost, "ISLA: Temporal Segmentation and Labeling for Audio-Visual Emotion Recognition," in IEEE Transactions on Affective Computing, vol. 10, no. 2, pp. 196-208, 1 April-June 2019, doi: 10.1109/TAFFC.2017.2702653.

[13] C. Qing, R. Qiao, X. Xu and Y. Cheng, "Interpretable Emotion Recognition Using EEG Signals," in IEEE Access, vol. 7, pp. 94160-94170, 2019, doi: 10.1109/ACCESS.2019.2928691.

[14] C. Qing, R. Qiao, X. Xu and Y. Cheng, "Interpretable Emotion Recognition Using EEG Signals," in IEEE Access, vol. 7, pp. 94160-94170, 2019, doi: 10.1109/ACCESS.2019.2928691

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