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AETIOLOGY ON EMOTION RECOGNITION STRATEGIES USING VIDEO, ELECTROENCEPHALOGRAM AND PHYSIOLOGICAL SIGNALS

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Abstract: **Multimodal emotion recognition is a research area that involves using signals of various natures, such as facial expressions, speech, gestures, and physiological signals, to recognize emotions accurately. This field has gained importance due to its potential applications in decision-making, human recognition, and social interaction. One of the significant challenges in multimodal emotion recognition is feature extraction, which involves identifying the relevant features from the signals that carry emotional information. Various techniques have been developed for feature extraction, including machine learning-based methods, such as deep learning, feature fusion, and feature selection. These techniques aim to extract the most relevant and discriminative features from the signals to improve the accuracy of emotion recognition.**

Keywords: **Emotion recognition, multimodal signals, deep learning, fusion-based techniques, classification accuracy.**

I. INTRODUCTION

Emotions are a combination of physiological and mental expressions that result from different faculties and thoughts[1]. Positive emotions such as excitement and happiness, and negative emotions like anger and sadness, have a visible impact on human behavior. Emotion recognition is a crucial factor applied in effective computing to create an efficient environment for man-machine interactions[1,14].To achieve effective man-machine interactions, researchers have utilized several pieces of information that signify emotions[2]. Changes in people's emotions can cause mental, behavioral, and physical changes. Facial expressions, posture, physiological responses, and voice signals are some of the means through which individuals communicate their emotions[5,6,7,8]. Additionally, deeper insights can be gleaned from the way people interact with others.

As of now, a portion of the specialists began their concentrate on Emotion acknowledgment in view of multimodal signals, yet at the same time the absence of key highlights and element overt repetitiveness issues of multimodal combination need to settled [42].

Valence and arousal are the commonly used dimensional spaces for emotion recognition, which define emotions based on the level of activation or arousal and the negativity or positivity of the emotional state. These dimensional spaces are often used in AI-based techniques for emotion recognition[7].

Regression and classification techniques have been extensively studied in previous works, where valence or arousal space is used to recognize basic emotions. However, some emotions overlap, and common personal states are not well differentiated based on classification. In recent years, Deep Neural Networks (DNNs) have been introduced in emotion recognition, and their results show better performance compared to shallow techniques [5,7,13,51].

Moreover, several multimodal architectures have been designed to take advantage of the benefits of both approaches, which can be categorized into two classes: supervised and joint. In supervised multimodal architectures, each modality is processed separately, and the results are combined using fusion techniques. In joint architectures, all modalities are processed simultaneously, and the results are integrated at a later stage. These multimodal architectures have shown promising results in improving the accuracy of emotion recognition systems.

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The main objective of this review is to provide a comprehensive study of various emotion recognition methodologies considering multimodal signals. Based on emotion classification, current designs are categorized into deep learning, multimodal system, and fusion, among others. This review considers traditional methods for emotion recognition for analysis purposes. The study is carried out by considering methodology used, recognition rate and datasets used. Additionally, performance evaluation measures are considered for evaluating the performance of the proposed emotion recognition techniques.

This article is arrangedas follows:Section 2 elaborates Comparison study and Feature Direction and section 3 shows the issues faced by conventional techniques. Section 4 discussed the analysis of techniques with respect to performance metrics, toolset, year of publication, and concludes the paper in section 5.

II. COMPARATIVE STUDY AND FEATURE DIRECTION

The review of numerous emotion recognition strategies is described in this section. Table 1 will demonstrate the feature extractions techniques on video, EEG and Physiological inputs.

Table 1. Different Types of Features, Classifier and Dataset in Video Emotional Recognition System

Ref	Feature Extraction Methods	Recognition rate	Types of Dataset	Methods
[4]	Convolution Neural Network	78.9 %	AVEC 2016 & RECOLA	Long short-term memory
[5]	Context sensitive technique	72 %	IEMOCAP	Hidden Markov Models
[6]	Gabor Wavelet Transform	90.4 %	Speech & Faces	Backpropagation Neural network
[12]	cascading 3-dimensional convolution neural networks (C3Ds) and deep belief networks (DBNs)	83.34 %	eNTERFACE and FABO	Bilinear pooling
[15]	3D Convolution – Long Short Term Memory	96.75% & 78.75 %	MOUD and IEMOCAP	CNN-RNN Hybrid Model
[17]	Fuzzy CNN	83.2 %	Movie Clips	Convolution Neuro-fuzzy network
[18]	Bidirectional Principal Component Analysis & Least square LDA	90.83% & 86.67 %	RML & eNTERFACE'05	Optimized Kernel-Laplacian Radial basis Function
[19]	Fusion Method	92.22%	DEAP	Hybrid Fusion Method
[22]	Canonical corelation	71.03 %	eNTERFACE	Support Vector Machine
[26]	PRAAT	80 %	Spontaneous Filipino	Support Vector Machine
[27]	Canonical corelation	85 %	DEAP	Proposed CCA
[28]	MFCC	71.8 %	IEMOCAP	RNNs
[29]	Statistical functionals	75.5 %	IEMOCAP	Deep Neural Network
[35]	Statistical methods	83.10 %	emoFBVP	Deep Belief Network
[38]	Deep spatio-temporal	83.34 %	eNTERFACE	Deep Belief Network
[39]	Information Fusion	84 %	eNTERFACE	kernel entropy component analysis

Table 2. Different Types of Features, Classifier and Dataset in EEG& Physiological Emotional Recognition System

Ref	Types of Features	Recognition rate	Types of Dataset	Methods
[1]	PSD(Power Spectral Density) Differential Entropy	91.01% & 83.25%	SEED & DEAP	Bimodal Deep Autoencoder & SVM linear classifier
[3]	Blood Volume Pressure, Skin Temperature & GSR	84.18% & 83.04 %	DEAP	Multiple Fusion layer based stacked autoencoder
[7]	masseter muscle, blood volume pressure, skin conductance	72.1 %	MIT Media Lab	Fusion Method

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[8]	GSR, ECG and RSP	72.93 %	1500 Video Clips	Attention- LSTM
[9]	GSR,EEG	82.92 %	DEAP	Ensemble Convolution Neural Network
[11]	EEG,GSR	73.9 %	AMIGOS	LSTM-RNN
[13]	EEG, GSR,BVP, EMP & EOG	81.45 %	DEAP	Short Term Fourier Transform
[14]	EEG and Physiological signals	92.07 %	DEAP	Convolution Auto- Encoder
[24]	EEG, ECG, EOG	75.19 %	Biosensor Network	Reputation-driven Support Vector Machine (RSVM)
[40]	Physiological signals	70.28 %	DEAP	LDC and K-NN Cascade Architectures
[43]	EEG and Physiological signals	92.87 %	DEAP	LSTM Networks
[44]	EEG	83.13 %	SEED	Dual-tree Complex Wavelet Transform
[51]	EEG and Physiological signals	87.94 %	DEAP	DEEP Recurrent Neural Network

III. RESEARCH GAPS AND ISSUES

This section highlights the gaps and issues faced by previous emotion recognition methods using different input modalities. The research issues of deep learning approaches are discussed as follows:

The method in [2] failed to consider other deep learned visual and audio features for enhancing baseline systems more effectively. Dynamic modelling of low-level features was not investigated using multimodal LSTM for improving the recognition rate better [5].The method failed to consider other NN for identifying and enhancing the accuracy of the audio emotion [15].The method in [43] does not consider other modalities, like labor concentration, sleep stages analysis, and the driving fatigue for better performance. In [35], a real-time multimodal emotion recognition system was not considered based on deep learning architecture for enhancing classification accuracy. The method in [4] failed to include more modalities, such as physio for improving the performance of the emotion recognition. More efficient features were not identified in [6] for enhancing the performance of the system. In [1], the method does not investigate eye movement features for better system performance. The effective data augmentation method was not considered for generating the feature vectors [3].Other datasets were not considered in [14] for improving the stability of the system. Ensemble recurrent neural network was not considered in [9] for identifying the emotions due to peripheral physiological and EEG signals being time series data. The method [17] failed to consider other fuzzy operators in deep recurrent neuro-fuzzy network and deep convolutional neuro-fuzzy networks to improve the system performance. The method in [47], detects the class accurately, but failed to enhance the interaction experience. In [49], another advanced score fusion technique, such as the logistic regression method, was not included in the popular FoCal toolkit for improving the system performance.

These challenges and gaps identified in previous studies highlight the need for further research and development in the field of emotion recognition using multiple inputs. It is necessary to investigate and develop deep learning approaches that consider other visual and audio features for enhancing baseline systems more effectively, and dynamic modelling of low-level features using multimodal LSTM for better recognition rates. Additionally, exploring other neural network architectures for identifying and enhancing the accuracy of the audio emotion can also be helpful. Further research should also consider other modalities, such as physiological signals and eye movements, for improving the performance of emotion recognition systems [18,44,45].

It is also important to address challenges in machine learning approaches, such as finding appropriate parameters and labelling strategies, and testing other classification systems based on features to improve the generality and discernibility of the system. Moreover, considering advanced genetic programming principles and transfer learning can also help in enhancing the accuracy and generalizability of emotion recognition systems [19,40].

In terms of fusion techniques, it is necessary to investigate DNN for enhancing the output obtained from textual modality and explore end-to-end learning to speed up the emotion recognition system performance. Furthermore, considering other factors such as elicitation styles, languages, and cultural backgrounds can enrich the modelling power of the fusion architecture [11,16,31,37].

Overall, addressing these challenges and gaps can lead to the development of more accurate, efficient, and generalizable emotion recognition systems using multimodal signals.

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IV. CONCLUSION

Overall, this survey provides a comprehensive overview of the different techniques used for emotion recognition using multiple inputs like Video, EEG and Physiological signals and highlights the gaps and issues in current research. The analysis of the papers based on feature extraction methods, recognition rate, types of data set used and different deep learning techniques are applied on video and EEG and Physiological inputs. This analysis can be helpful for researchers in this field. The identification of the main drawbacks and areas for improvement in current research can guide future studies towards developing more effective emotion recognition strategies. By addressing these gaps and issues, it is possible to create more accurate and efficient emotion recognition systems that can be applied in various fields such as healthcare, education, and entertainment.

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