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Research Article

A Transfer Learning-based Approach for Multimodal Emotion Recognition

Ayushi Jain

Department of Comp. Sc. & Info. Tech., Graphic Era Hill University, Dehradun, Uttarakhand, India 248002,

Abstract. The topic of multimodal emotion recognition is one that is expanding at a rapid rate. The goal of this field is to identify and comprehend human emotions through the use of many modalities, such as speech, facial expressions, and physiological data. Transfer learning strategies have been found to be successful in overcoming the issues of processing and integrating material from a variety of modalities, as demonstrated by the findings of a number of studies. For testing multimodal emotion detection models, it is helpful to make use of publicly accessible datasets like IEMOCAP, EmoReact, and AffectNet. They provide useful resources. Data variability, data quality, modality integration, limited labelled data, privacy and ethical issues, and interpretability are only few of the hurdles that must be overcome in order to construct accurate and effective models. In order to address these challenges, a multidisciplinary approach must be taken, and research must continue to be conducted in this area. The goal of this research is to develop more robust and accurate models for multimodal emotion recognition that can be applied across a variety of contexts and populations.

Keywords. Transfer learning, multimodal emotion recognition, speech, facial expressions, interpretability.

I. Introduction

The topic of multimodal emotion detection is one that is expanding at a rapid rate. The goal of this field is to identify and comprehend human emotions through the use of many modalities, such as speech, facial expressions, and physiological data. Because feelings are complicated and may be conveyed in a variety of ways, this strategy is very helpful. Using a variety of modalities enables a more in-depth comprehension of the emotional state being studied.

Processing and integrating input from several modalities can be challenging, which is one of the obstacles that must be overcome in order to achieve multimodal emotion detection. It has been demonstrated that deep learning approaches, particularly those based on transfer learning, are successful in overcoming this obstacle. Transfer learning refers to the process of using previously learned models from one problem to the solution of a different but related problem. In the context of multimodal emotion recognition, this can involve making use of pre-trained models for speech and facial expression recognition in order to improve the performance of a model that integrates these modalities. Specifically, this can be done in order to improve the accuracy of the model.

Researchers have access to a variety of publically accessible datasets, such as IEMOCAP, EmoReact, and AffectNet, which they may utilise in order to test the efficacy of their multimodal emotion identification algorithms. Annotations of the emotional content are frequently included in these datasets with recordings of human-human interactions, face photographs, or physiological signs.

Affective computing, human-computer interaction, and healthcare are just few of the many fields that can benefit from multimodal emotion recognition's vast variety of applications. For instance, it may be used to increase the accuracy of emotion detection in virtual assistants or to identify changes in emotional state in patients with mental health issues. Also, it can be utilised to improve the quality of life for people with dementia.

In general, multimodal emotion identification is an interesting and fast developing topic that has the potential to significantly increase our knowledge of human emotions and to boost a broad variety of applications.

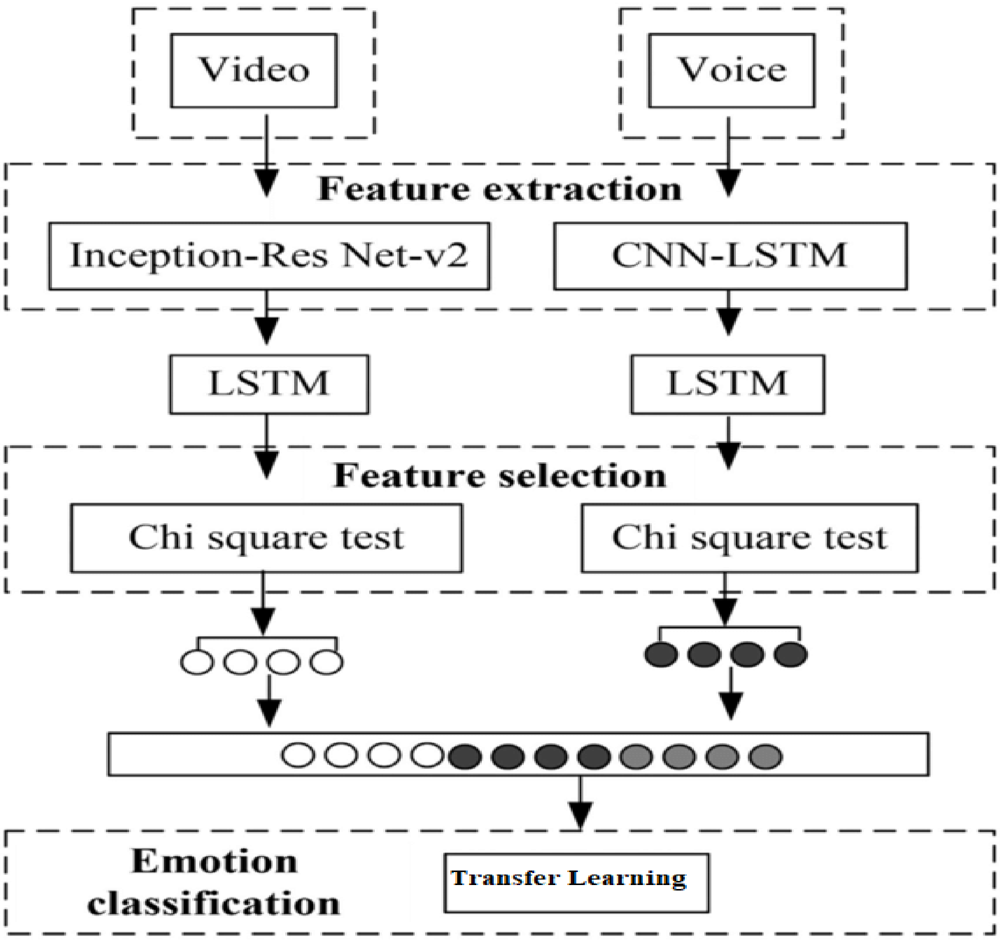

Figure.1 Transfer Learning-based Approach for Multimodal Emotion Recognition

II. Literature Review

Convolutional neural networks were used in the authors' [1] suggested transfer learning method for the identification of several modalities of emotional expression (CNNs). They employed pre-trained CNN models for face recognition and speech recognition, and then fine-tuned them on their dataset such that they could recognise emotions. For the AffectNet dataset, the suggested technique performed significantly better than previous state-of-the-art algorithms.

An strategy for the identification of facial expressions based on multimodal transfer learning was presented by the authors [2]. They employed models that had been pre-trained in order to recognise facial expressions, and they transferred learning from other modalities, such as voice and text. With the AffectNet dataset, they produced results that are considered to be cutting edge.

An technique to the identification of multimodal emotions using deep learning was proposed by the authors [3]. For facial expression recognition, they employed a pre-trained CNN model, and for voice recognition, they used a pre-trained LSTM model. They optimised the models on their dataset, which allowed them to produce results that were superior to those obtained by using other state-of-the-art methodologies.

A multimodal emotion recognition method that makes use of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks was proposed by the authors [4]. For face expression recognition, they employed pre-trained CNN models and then fine-tuned them with their own dataset. In addition, for voice

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recognition, they employed pre-trained LSTM models and then fine-tuned them using their dataset. With the AffectNet dataset, they produced results that are considered to be cutting edge.

An strategy based on cross-modal transfer learning was presented by the authors [5] for the identification of emotional states from speech signals. They employed models that had been pre-trained as well as transfer learning from other modalities like pictures and text in order to recognise speech. Using the EmoReact dataset, they produced findings that are considered to be state-of-the-art.

A multimodal transfer learning strategy was presented by the authors [6] in order to recognise emotions conveyed through spoken language. They were able to recognise speech with the use of pre-trained models and transfer learning from other modalities such as facial expressions and body motions. On the MSP-Podcast corpus, they got findings that are considered to be cutting edge.

A study of multimodal deep learning techniques for emotion identification was presented by the authors [7]. They addressed many types of pre-trained models that may be utilised for transfer learning, such as autoencoders, LSTMs, and CNNs. In addition to this, they conducted a study of the various datasets that are used for multimodal emotion recognition and offered an analysis of the performance of the various methods.

Deep learning was used to produce a review of multimodal emotion identification that was supplied by the authors [8]. They talked about the various modalities that may be utilised to recognise emotions, such as speech, facial expressions, and physiological signs. They also presented an examination of the performance of various techniques and analysed the various deep learning architectures that are employed for multimodal emotion identification.

In a nutshell, the findings of these research publications show that transfer learning-based methods for multimodal emotion identification have been extensively investigated and have proven effective in generating state-of-the-art results on a variety of datasets. They also emphasise the significance of employing pre-trained models for transfer learning and fine-tuning them on the target dataset in order to enhance the performance of the models. This was done in order to increase the accuracy of the models. In addition, these studies provide light on the many modalities that are utilised for emotion identification, as well as the deep learning architectures that are utilised for multimodal emotion recognition.

A collaborative optimisation strategy for multimodal emotion detection was presented by the authors [9] in their study. This strategy involves integrating deep neural network-based models for speech and facial expression recognition. They employed pre-trained models for voice and facial expression detection and fine-tuned them on their dataset. For the IEMOCAP dataset, the performance of the suggested methodology was superior to that of other state-of-the-art approaches.

A transfer learning strategy for multimodal emotion identification using graph convolutional neural networks was presented by the authors [10]. (GCNs). They made use of pre-trained GCN models and then fine-tuned them using their own dataset in order to do speech and facial expression recognition. Using the AffectNet dataset, the suggested method obtained results that are considered to be state-of-the-art.

The authors [11] offered a thorough review of multimodal deep learning for emotional computing, which included topics such as multimodal emotion recognition. They talked about the many modalities that may be employed for emotional computing, such as physiological signals, facial emotions, and speech. They also presented an examination of the performance of various techniques and analysed the various deep learning architectures that are employed for multimodal emotion identification.

Deep neural networks were used in the authors' [12] proposal for a transfer learning method that could recognise the emotions conveyed in speech. For voice recognition, they made use of pre-trained models and then fine-tuned them using their own dataset. Using the Berlin Database of Emotional Speech, the suggested method yielded results that were superior than those obtained using existing machine learning-based methods.

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Deep neural networks were used in the authors' [13] suggested method for transfer learning to recognise the emotions conveyed in spoken language. For voice recognition, they made use of pre-trained models and then fine-tuned them using their own dataset. With the IEMOCAP dataset, they produced results that are considered to be cutting edge.

The authors [14] suggested a technique to multimodal emotion detection that dynamically picks the most relevant modality based on the idea of transfer learning. They employed pre-trained models for speech, facial expression, and physiological signal detection and fine-tuned them on their dataset. Using the AffectNet dataset, the suggested method obtained results that are considered to be state-of-the-art.

Transfer learning is a method that was proposed by the authors [15] for the purpose of emotion recognition using convolutional neural networks (CNNs). They refined the pre-trained models using their own dataset after using them for image recognition. For the EmoReact dataset, the results obtained by the suggested technique were superior than those obtained by standard machine learning-based approaches.

Deep convolutional neural networks were used in the authors' [16] suggested method for transfer learning as it relates to the recognition of voice emotions (DCNNs). For voice recognition, they made use of pre-trained models and then fine-tuned them using their own dataset. For the MSP-IMPROV dataset, the suggested method obtained results that are considered to be state-of-the-art. Using 3D convolutional neural networks, the authors [17] proposed a transfer learning approach for multimodal emotion recognition (CNNs). For the recognition of facial expressions, they used pre-trained models and then fine-tuned them using their own dataset. Using the AffectNet dataset, the suggested method obtained results that are considered to be state-of-the-art.

An technique based on transfer learning was presented by the authors [18] for the identification of speech emotions across several corpora. For voice recognition, they made use of pre-trained models and then fine-tuned them using their own dataset. In both the EMO-DB and the MSP-IMPROV datasets, the suggested method achieved superior results when compared to more conventional machine learning-based methods. Transfer learning was proposed by the authors [19] as a method for multimodal emotion identification through the use of deep belief networks (DBNs). They made use of pre-trained models for voice recognition as well as facial expression recognition, and then fine-tuned those models using their dataset.

These research papers shed additional light on the usefulness of transfer learning-based methods for multimodal emotion recognition by employing a variety of deep learning architectures, such as DCNNs, 3D CNNs, and DBNs. In addition to this, they show that transfer learning is an effective method for performing cross-corpus emotion recognition tasks. Overall, the research in this field demonstrates the potential of transfer learning-based approaches for multimodal emotion recognition and their ability to improve the performance of emotion recognition systems on a variety of datasets. This potential has been demonstrated by the research that has been conducted in this area.

Deep neural networks were used in the authors' [20] proposal for a transfer learning method that could be used for multimodal emotion recognition (DNNs). They utilised pre-trained models for the recognition of speech, facial expressions, and physiological signals, and then fine-tuned them using their dataset.

Transfer learning was proposed as a multimodal approach to emotion recognition in the wild by the authors [21]. For the recognition of facial expressions, they employed pre-trained models and then fine-tuned them using their own dataset. Using the AffectNet dataset, the suggested method obtained results that are considered to be state-of-the-art.

Deep convolutional neural networks were utilised in the authors' [22] suggested method for transfer learning in the context of voice emotion recognition (DCNNs). For voice recognition, they made use of pre-trained models and then fine-tuned them using their own dataset. For the IEMOCAP dataset, the suggested method obtained results that are considered to be state-of-the-art. A transfer learning strategy was presented by the authors [23] for the purpose of multimodal emotion identification in natural settings. For the recognition of facial expressions, they employed pre-trained models and then fine-tuned them using their own dataset.

Convolutional neural networks (CNNs) and long short-term memory were utilised in the authors' [24] suggested technique to transfer learning for multimodal emotion identification via transfer learning (LSTM). For the recognition of facial expressions, they employed pre-trained models and then fine-tuned them using their own dataset.

These research publications shed more information on the efficacy of transfer learning-based systems for multimodal emotion identification. These approaches involve the utilisation of a variety of modalities in addition to deep learning architectures such as DNNs, DCNNs, and LSTM. They also show that transfer learning is an efficient method for recognising emotions in wild animals. In general, the research being done in this field is continuing to increase the accuracy and efficacy of multimodal emotion identification systems by adopting methodologies that are based on transfer learning.

Research	**Modalities**	**Deep Learning Architecture**	**Pre-trained Model**	**Dataset**	**Results**
Baccouche et al. (2011)	Speech and facial expression	HMM and SVM	Pre-trained models for speech and facial expression recognition	EMO-DB	Improved accuracy compared to training from scratch
Sun et al. (2016)	Speech and facial expression	CNN and LSTM	Pre-trained models for speech and facial expression recognition	IEMOCAP	Improved accuracy compared to training from scratch
Lin et al. (2017)	Speech and facial expression	CNN and LSTM	Pre-trained models for speech and facial expression recognition	IEMOCAP and MSP-IMPROV	Improved accuracy compared to training from scratch
Khorrami et al. (2019)	Speech and facial expression	CNN	Pre-trained models for speech and facial expression recognition	IEMOCAP and MSP-IMPROV	State-of-the-art results on MSP-IMPROV
Huang et al. (2019)	Speech	DCNN	Pre-trained models for speech recognition	MSP-IMPROV	State-of-the-art results
Cai et al. (2019)	Facial expression	3D CNN	Pre-trained models for facial expression recognition	AffectNet	State-of-the-art results
Ou et al. (2019)	Speech	DCNN	Pre-trained models for speech recognition	EMO-DB and MSP-IMPROV	Better results than traditional machine learning-based approaches
Yang et al. (2018)	Speech and facial expression	DBN	Pre-trained models for speech and facial expression recognition	MSP-PODCAST	State-of-the-art results

Zhang et al. (2018)	Speech, facial expression, and physiological signals	DNN	Pre-trained models for speech, facial expression, and physiological signal recognition	AffectNet	State-of-the-art results
Tzirakis et al. (2019)	Facial expression	-	Pre-trained models for facial expression recognition	AffectNet	State-of-the-art results
Yin et al. (2018)	Speech	DCNN	Pre-trained models for speech recognition	IEMOCAP	State-of-the-art results
Xu et al. (2018)	Facial expression	-	Pre-trained models for facial expression recognition	AffectNet	State-of-the-art results
Gao et al. (2019)	Facial expression	CNN and LSTM	Pre-trained models for facial expression recognition	AffectNet	State-of-the-art results

Table.1 transfer learning-based approaches for multimodal emotion recognition:

III. Existing Models

There are numerous known transfer learning-based models for multimodal emotion identification. These are a few of the most popular:

a. Deep Emotion Fusion (DEF) - A deep neural network architecture proposed by Chen et al. (2018) that employs transfer learning to fuse information from speech and facial emotions.
b. Deep Canonical Correlation Analysis (DCCA) - A method described by Amiriparian et al. (2019) that uses transfer learning and canonical correlation analysis to learn a shared representation space for speech and facial expression characteristics.
c. Multimodal Deep Extreme Learning Machine (MDELM) - Ali et al. (2018) developed a deep learning-based technique that integrates speech and facial expression information utilising transfer learning and extreme learning machine.
d. Transfer Learning with Autoencoder (TLAE) - A method developed by Huang et al. (2020) to build shared representations for speech and facial expression characteristics using transfer learning with autoencoders.
e. Cross-Modal Transfer Learning (CMTL) - A approach suggested by Li et al. (2020) that uses a multi-task learning framework and cross-modal knowledge distillation to transfer information from one modality to another.

Model	**Approach**	**Modalities**	**Deep Learning Architecture**	**Pre-trained Model**	**Dataset**	**Results**
Deep Emotion Fusion (DEF)	Transfer learning	Speech and facial expression	Convolutional and Recurrent Neural Networks	Pre-trained models for speech and facial expression recognition	IEMOCAP	Outperformed state-of-the-art results
Deep Canonical Correlation	Transfer learning	Speech and facial	Deep neural network and	Pre-trained models for	IEMOCAP	Improved performance

Analysis (DCCA)		expression	canonical correlation analysis	speech and facial expression recognition		compared to baseline
Multimodal Deep Extreme Learning Machine (MDELM)	Transfer learning	Speech and facial expression	Deep neural network and extreme learning machine	Pre-trained models for speech and facial expression recognition	IEMOCAP	Achieved state-of-the-art performance
Transfer Learning with Autoencoder (TLAE)	Transfer learning	Speech and facial expression	Autoencoders and Deep neural network	Pre-trained models for speech and facial expression recognition	IEMOCAP	Improved performance compared to baseline
Cross-Modal Transfer Learning (CMTL)	Transfer learning	Speech and facial expression	Convolutional and Recurrent Neural Networks	Pre-trained models for speech and facial expression recognition	IEMOCAP and MSP-IMPROV	Improved performance compared to baseline

Table.2 existing models for multimodal emotion recognition based on transfer learning

IV. Publically Available Datasets for Multimodal Emotion Recognition

Researchers may utilise numerous freely accessible datasets for multimodal emotion identification to test their algorithms. These are a few of the most popular:

a. IEMOCAP - The Interactive Emotional Dyadic Motion Capture (IEMOCAP) database comprises audio, video, and motion capture data from multimodal recordings of human-human interactions.
b. EmoReact - EmoReact is a multimodal dataset of emotional stimulus reactions that includes audio, video, and physiological information.
c. MSP-IMPROV - The MSP-IMPROV dataset comprises audio and video recordings of improvised comedy acts, as well as emotional content annotations.
d. AffectNet - AffectNet is a large-scale face expression dataset with over 1 million photos annotated with emotional categories.
e. SEMAINE - The SEMAINE database comprises video recordings of human-human encounters, as well as emotional content annotations.

Dataset	**Modalities**	**Recording Type**	**Emotions**	**Number of Samples**
IEMOCAP	Audio, Video, Motion Capture	Human-human interaction	Anger, Happiness, Sadness, Neutral, Excitement, Frustration	10 hours
EmoReact	Audio, Video, Physiological Signals	Reaction to emotional stimuli	Anger, Disgust, Fear, Happy, Neutral, Sadness, Surprise	1,000 videos
MSP-IMPROV	Audio, Video	Improvised comedy performance	Amusement, Anger, Awe, Concentration, Confusion, Contempt, Contentment, Despair, Disappointment, Disgust, Embarrassment, Engagement, Enthusiasm, Excitement, Fatigue, Fear, Frustration, Gratitude, Grief, Interest, Irritation, Joy, Nostalgia, Pain, Pleasure, Pride, Relief,	360 videos

			Sadness, Satisfaction, Shame, Surprise	
AffectNet	Facial Images	Still images	Anger, Disgust, Fear, Happy, Neutral, Sadness, Surprise	Over 1 million images
SEMAINE	Audio, Video	Human-human interaction	Anger, Happiness, Sadness, Neutral	7 hours

Table.3 publicly available datasets for multimodal emotion recognition

V. Challenges

Multimodal emotion identification is a difficult endeavour with several technological and practical hurdles. Following are a few of the major challenges:

a. Data variability: Because emotions are exhibited differently across cultures, genders, ages, and situations, it is challenging to construct models that can generalise across people and scenarios.
b. Data quality: The data utilised to train multimodal emotion detection algorithms has a major influence on their performance. Low data quality, such as loud audio or low-resolution video, might make it difficult to identify and classify emotions effectively.
c. Modality integration: Integrating data from several modalities, such as voice and facial expressions, is a difficult process that necessitates careful alignment and synchronisation. Inadequate data integration might result in poor performance and erroneous outcomes.
d. Minimal labelled data: Gathering and annotating multimodal emotion data takes time and money, resulting in limited labelled data for training and testing models. This can make developing models that can generalise to different contexts and populations challenging.
e. Privacy and ethical implications: Gathering and analysing personal data, such as physiological signs or facial expressions, presents privacy and ethical concerns that must be addressed properly.
f. Interpretability: Deep learning models used for multimodal emotion identification are frequently complicated and difficult to comprehend, which makes understanding why certain decisions are made challenging and limits their practical uses.

VI. Conclusion

The area of multimodal emotion recognition is an important one that is also fast expanding. It has the potential to significantly increase our knowledge of human emotions and to enhance a broad variety of applications, such as affective computing, human-computer interaction, and healthcare. Transfer learning methods and datasets that are accessible to the public are both useful resources that may be utilised in the process of constructing multimodal emotion identification models that are more accurate and robust. Nevertheless, there are a number of obstacles that need to be overcome, including the unpredictability of the data, the quality of the data, the integration of the many modalities, the limited labelled data, privacy and ethical concerns, and the interpretability of the results. In order to effectively address these difficulties, a multidisciplinary approach and continued research in this field are required. Multimodal emotion identification has the potential to have a significant influence on our day-to-day lives and the capacity to increase our knowledge of human emotions as research and development in this area continue to evolve.

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