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Research Article

Comparative Study on Model Emotion Identification Through Facial Expressions

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ABSTRACT

Facial expressions play a crucial role in human communication because they may convey a wide spectrum of emotions. The act of communicating or expressing particular feelings, objectives, or ideas is called expression. The tremendous advancements in technology, particularly in the domains of computer vision and artificial intelligence, have expedited efforts to develop suitable models for emotion recognition from facial expressions. This systematic literature review aims to provide an in-depth analysis of the models that are being utilized for this project. A thorough search turned up a number of research that were looked at in order to gather information about improving face recognition. This paper covers a wide range of approaches, from simple deep learning frameworks to sophisticated machine learning algorithms. The findings provide insight into the evolution of techniques, challenges faced, and future directions in the field of facial expression-based emotion recognition. These data will subsequently serve as the foundation for additional study that examines participant emotions or expressions throughout a training exercise.

Keywords: Computer Vision, Facial expression, Emosion expression, Emotion recognition, Systematic Literature Review.

INTRODUCTION

Expression is an expression or process in expressing or conveying certain feelings, intentions, or ideas [1]. Through facial expressions, the turmoil and emotional state within a person has the potential to be understood [2]. Facial expression (mimic) is a form of nonverbal communication that represents the movement or position of muscles on the face that can represent the emotional state of a person that can be observed visually. Mehrabian states that facial expressions contribute 55% to the nonverbal communication process, voice contributes 38% and language contributes 7% [3]. Human communication is inherently multifaceted, with emotions serving as a cornerstone in conveying nuanced expressions and intentions [4]. Among the myriad channels through which emotions are conveyed, facial expressions stand out as one of the most prominent and universally understood mediums [4]. The ability to accurately decipher these facial cues not only enriches interpersonal interactions but also holds immense potential for applications across various domains, ranging from healthcare to human-computer interaction [5]. With the advent of sophisticated technologies, particularly in the realms of artificial intelligence and computer vision, the endeavor to automate the process of emotion identification through facial expressions has gained substantial traction [6]. Emotion recognition through facial expressions entails the development of computational models capable of discerning and categorizing the underlying emotional states depicted in facial images or videos [7]. This task is inherently complex, as it necessitates the extraction of subtle visual cues embedded within facial features [8], such as eyebrow movements [9], eye widening, or lip curvature. Traditionally, human experts have been relied upon for the interpretation of these cues [10]. However, the advent of machine learning and deep learning techniques has paved the way for automated systems that can emulate, and in some cases, surpass human-level performance in this domain [11].

LITERATURE REVIEW

Many studies have addressed the recognition of emotions during learning, including practice education [12] [13]. According to Ainley, emotions play a crucial role in determining the character of educational experiences including motivation for learning and cognitive processes [14]. While emotions, motivation, and cognition may all be theoretically and experimentally dissected and explained independently, these three ideas must be seen as interconnected variables in order to fully comprehend students' knowledge and skill sets [15].

People are able to infer from others' facial expressions what they are feeling emotionally [16]. Unfortunately, there are limits to how quickly and accurately humans can capture these moments [17]. Goals are emphasized in motivation. The achievement (achievement) gained can be determined by the goals that have been set and the motivations for achieving these goals [18]. Setting goals can boost motivation if the following circumstances are met. First of all, the objective is well-defined, with a distinct schedule as one of its features. Second, objectives should be hard but logical to accomplish. Thirdly, objectives are restricted by the desired outcomes.

An individual may have emotions as a result of an event. This is an honest feeling. Sometimes a person experiences emotion as a result of something that happened to another person. This feeling is vicarious. Certain vicarious emotional experiences involve feeling the same emotion as the person experiencing it. We refer to these situations where we experience emotion because we are experiencing the same emotion as someone else as empathy [19], [20], [21].

A multidisciplinary topic called "affective computing" [22] emphasizes how computers can perceive, understand, and react appropriately to human emotions. In order to foster more human-centered interactions, Picard stresses the significance of incorporating emotional intelligence into computing systems. Motivation is an emotional aspect of learning that is inextricably linked to the essential elements of students' academic performance. Emotions and motivation are inextricably linked. The relationship between affective computing and motivation in the context of education was highlighted in the context and linkage with affective computing [23].

Self-determination theory, which offers a fundamental framework for comprehending the interaction between motivation and emotion in the context of learning [24], supports the aforementioned claim in study. According to this idea, people are driven by deep-seated psychological desires for competence, autonomy, and intimacy [25]. According to this research, people are more likely to feel positive affect and intrinsic motivation when these demands are satisfied, which is in keeping with Pekrun's findings. Positive affect, or emotions of interest and pleasure, frequently goes hand in hand with actions linked to intrinsic motivation behaviors motivated by one's own interests and fulfillment as opposed to outside rewards. On the other hand, when these fundamental psychological requirements are not met, people may experience negative emotions and become motivated by outside factors, such as the desire for rewards or a desire to escape punishment. Establishing a welcoming and stimulating learning environment requires an understanding of and commitment to the relationship between affect and motivation [26].

Research explores the intricate relationship between motivation and feelings of achievement [27] [28]. They emphasized how emotions, which are an important aspect of affect, have an impact on future motivation in addition to being motivational outcomes [29]. While negative feelings like boredom or fear can stifle motivation, positive emotions like pride and joy are frequently linked to greater motivation and engagement. These reciprocal linkages imply that motivation maintenance and fostering in educational situations depend on a comprehension of and ability to regulate affective states [30] [31].

Systematically highlighting the importance of self-determination in student motivation and engagement [32], work also makes a contribution. Self Theory states that people act with varied degrees of autonomy and that motivation and pleasant affect are positively correlated with higher levels of autonomy. Positive affect, which supports intrinsic motivation and sincere interest in the learning process, is more likely to be felt by students in a learning setting where they feel like they have choice and control [33].

Secondly, studies emphasize how important emotional computing is for forming empathy in classroom settings [34] [35]. By identifying and reacting to emotional states, affective computing can aid in the creation of empathetic instructional tools [36][37]. This feature enables the system to adjust and offer assistance in accordance with the learner's emotional needs. Identifying and reacting to emotional clues in the context of face recognition can help teachers and educational technology show empathy [38][39], fostering a more encouraging and emotionally intelligent learning environment. In conclusion, the application of affective computing in the classroom has the potential to produce learning environments that are more flexible, engaging, and compassionate.

The field of face emotion recognition (FER) is gaining momentum in the study of human-computer interaction [40], [41], [42] with potential applications in the fields of education, digital entertainment, modern offices, customer service, driver monitoring, and emotional robotics [43][44]. The models and techniques used in in-depth research are becoming more and more varied [45][46][47]. In order to improve computer predictions [48], researchers in this subject are interested in creating methods for interpreting, encoding, and extracting facial expressions [49][50][51]. Deep learning applications have led to the use of several architectures for these methods in order to improve performance [52][53][53].

The majority of recent studies on the understanding of emotions typically use models based on the recognition of facial expressions as well as intonation or tone of voice [54][55], sometimes combining the two. When developing a Deep Convolutional Neural Network (DCNN) model to classify five distinct human facial emotions, for example, research employs the Covolutional Neural Network (CNN) method [56], [57], [58], [59]. The model's training and validation accuracy are comparable, and by reducing loss through the use of the Adaptive Momentum (ADAM) optimizer, accuracy is achieved up to 78.04% [60][61][62].

Hybrid features—that is, detection and classification algorithms that may be learned offline for real-time applications—are used in the research findings [63][64]. On a data set of static facial expressions in the wild (SFEW) and real-world affective faces (RAF) [65][66], the proposed method outperforms the reference method by 13% and 24%, respectively. The face detection process uses AdaBoost Cascade Classification and is extracted with Neighborhood Difference Features (NFD). A different study describes a method for recognising faces using motion history images (MHI) to extract expressive facial traits. MHI and 2D images work well together for video illumination and have implications for accuracy. In contrast, the suggested method in a study on automatic emotion recognition through audio visual achieved 74.3% accuracy for surprise emotion [67], 67.4% for disgust emotion, and 66.1% for sadness emotion utilizing a 2D CCN model for speech modality and a 3D CNN model for visual modality.

The Facial Action Coding System (FACS), which is a component of the Deep Convolutional Neural Network (DCNN) technique for human emotion representation, uses facial action units (FAUs) for detection [68]. "Dropout" is a regularization technique employed in the CNN layer that effectively lowers overfitting. This study has successfully classified eight basic emotion classes with an average accuracy rate of 92.81%; the lowest accuracy is the Anger class, which is 87.73%, and the highest is the Surprise class, which is 98.09%. The dataset used is called Extended Cohn Kanade (CK+), which is specifically for facial expression recognition [69]. When considered collectively, these sources demonstrate how deeply motivation and affect are entwined in learning environments. A pleasant affective state is reinforced by intrinsic motivation when basic psychological requirements are met, happy emotions are felt, and autonomy is felt.

METHOD

We conducted several experiments using EXPNet, MobileNetV2, InceptionV3, SimpleCNN methods for CK+ and FER2013 datasets. We found that EXPNet has the best accuracy compared to the models analyzed. The datasets that we use, we compare between the CK+ datasets (https://paperswithcode.com/dataset/ck) and FER2023 (https://www.kaggle.com/datasets/msambare/fer2013).

Some Expression Assessments on Trainees

Education and training are two ways to help educators and other staff members become more capable (Diklat). When delivering training, meeting the reference-based passing grade (Minimum Completeness Criteria) is the criterion for success in allowing participants to be deemed graduates. The three primary parts of the minimum completeness formulation are as follows:

1. attitude value,
2. knowledge score and

3. skill scores,

formulation used: Graduation= (30% Attitude Score)+(30% Knowledge Score)+(40% Skill Score)

Based on the results of the initial survey, attitude components that are frequently measured include empathy, motivation, accountability, confidence, participation, and motivation. On the other hand, four components are consistently selected as aspects that are challenging to measure directly: empathy, motivation, confidence, and participation. According to the graph that follows:

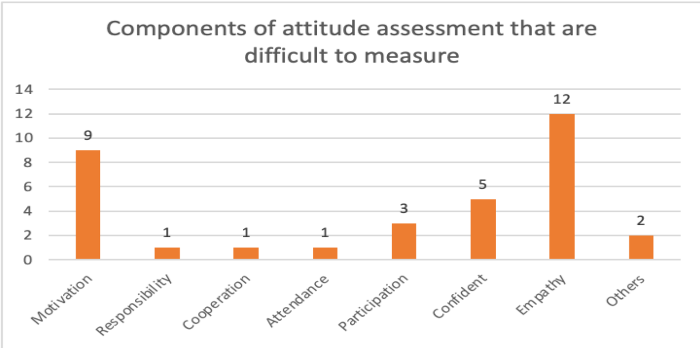

Fig 1. Components of attitude assessment that are often difficult to measure

Facial Emotion Recognition

1. Using public datasets, such as: FER2013.
2. Merging datasets, e.g. RAVDESS and Cohn_kanade
3. Creating a new dataset, creating a new dataset yourself.
4. Determine the facial emotion recognition algorithm
5. Building the Facial Emotion Recognition Model
6. Creating alternative models

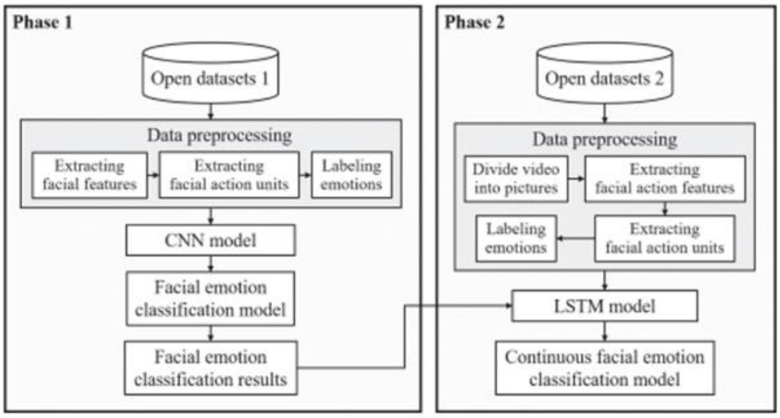

Fig 2. Alternative system architecture for Facial Emotion Recognition Model [70]

7. Comparing models, selecting the model with the best performance

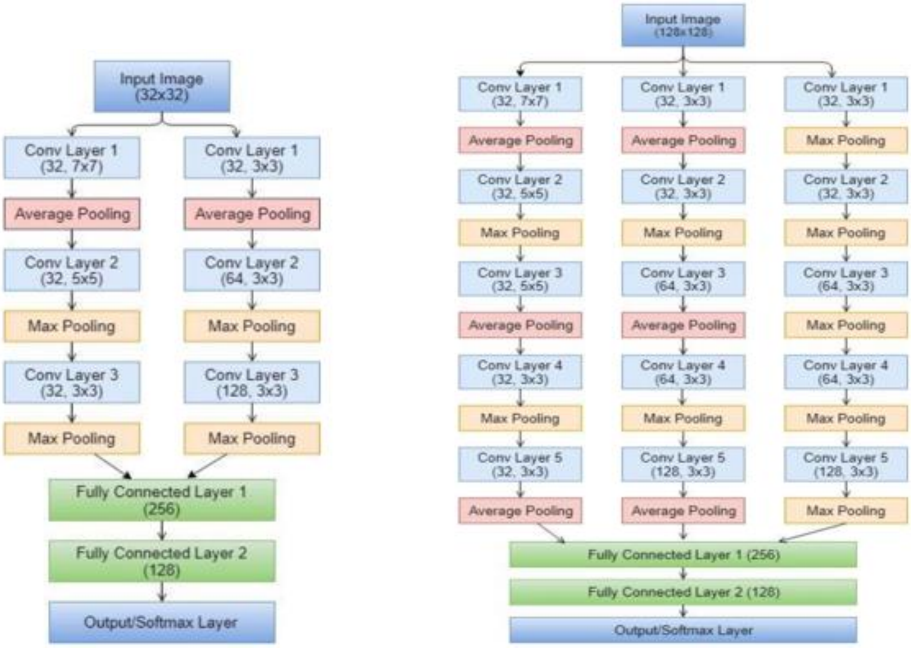

Fig 3. Comparing Models to get the best performance [73]

RESULT AND DISCUSSION

The results of our findings, we discovered that EXPNet had the best accuracy of 90% when compared to various other algorithms including MobileNetV2, InceptionV3, and Resmaking. These algorithms were tested using two datasets, CK+ and FER2013.

Dataset	Model	Val_Accuracy	Val_Loss
CK+	EXPNet	0.90	0.31
	MobileNetV2	0.83	0.58
	InceptionV3	0.88	0.35
FER	MobileNetV2	0.54	1.25
	Resmaking	0.45	1.48

The EXPNet model gets the highest accuracy which can be seen from figure 1 and Figure 2 below:

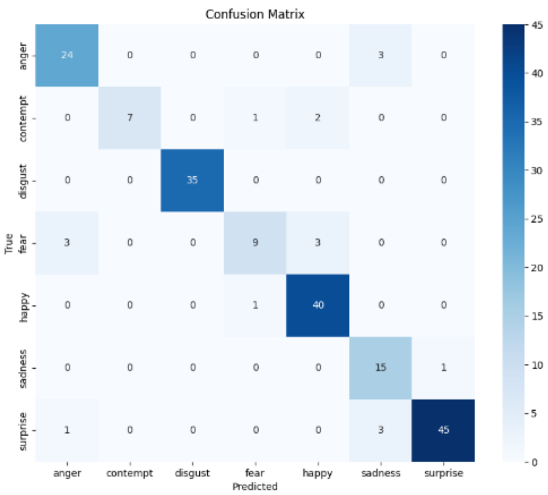

Fig. 1 Confusion matriks result

	precision	recall	f1-score	support
anger	0.86	0.89	0.87	27
contempt	1.00	0.70	0.82	10
disgust	1.00	1.00	1.00	35
fear	0.82	0.60	0.69	15
happy	0.89	0.98	0.93	41
sadness	0.71	0.94	0.81	16
surprise	0.98	0.92	0.95	49
accuracy			0.91	193
macro avg	0.89	0.86	0.87	193
weighted avg	0.91	0.91	0.91	193

Fig. 2 Performance model

DISCUSSION

EXPNet achieved the maximum accuracy of 90% in the investigation, which involved comparing the performance of several emotion detection algorithms using the CK+ and FER2013 datasets. Compared to the other examined algorithms, such as MobileNetV2, InceptionV3, and Resmaking, this result stands out. These results highlight the following points:

EXPNet's Superiority in Emotion Recognition: EXPNet attained notable precision, demonstrating its capacity to recognize and differentiate various facial emotions with a high level of precision. This implies that, in comparison to the other algorithms examined, the architecture or methodology employed by EXPNet might be more appropriate or successful for the task of emotion recognition.

Comparing EXPNet with Other Algorithms: While EXPNet is the most accurate algorithm, comparing it to MobileNetV2, InceptionV3, and Resmaking also reveals the relative advantages and disadvantages of each technique. These discrepancies in performance could be caused by elements like processing efficiency, architectural complexity, or the capacity to accommodate changes in facial expressions and ambient variables.

With an accuracy of 90%, EXPNet has a great degree of precision in recognizing facial expressions across the datasets it has been tested on. It implies dependable performance in differentiating facial expressions, which is essential for applications ranging from human-computer interaction to the recognition of emotions. It is critical to take into account the accuracy's generalizability to fresh, untested data as well as its consistency across various validation sets.

CONCLUSION

The dynamic landscape of emotion detection through facial expressions is highlighted by this comprehensive literature review, which concludes by presenting a colorful tapestry of approaches, difficulties, and prospects. The summary of results clarifies the noteworthy advancements achieved in using deep learning and machine learning methodologies to interpret the complex subtleties of human emotions expressed through facial expressions. Nevertheless, despite the advancements, enduring obstacles including cultural differences, data biases, and deployment limitations in the real world demand coordinated efforts and interdisciplinary teamwork to overcome. As long as projects like diversified dataset curation, algorithmic improvements, and multidisciplinary collaborations are given top priority, the area will be able to break through theoretical barriers and reach its revolutionary potential. Considering 90% accuracy, EXPNet outperforms other tested algorithms including MobileNetV2, InceptionV3, and ResNet, highlighting its status as a top facial expression recognition algorithm, according to the comparison analysis. This demonstrates how useful it could be in situations when precise facial expression recognition is needed. To evaluate its efficacy across larger datasets and a variety of real-world circumstances, however, further research is essential.

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